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SITUATIONAL AWARENESS FOR SURVEILLANCE AND INTERDICTION OPERATIONS (SASIO): TACTICAL INSTALLATION PROTECTION

by

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March 2010

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Security of a Forward Operating Base (FOB) is of high interest and operational importance to the U.S. military and allied forces. The Situational Awareness for Surveillance and Interdiction Operations (SASIO) model simulates the operational tasking of a single Unmanned Aerial Vehicle (UAV) and a ground-based interceptor that are designed to search, identify, and intercept potential hostile targets prior to reaching the FOB. This thesis explains the SASIO model and its implementation in JAVA. This theoretical model leverages Design of Experiments (DOE), which varies multiple characteristics of the system to explore insights for the tactical employment of UAV and interceptor to combat potential hostile actions against a predefined area of interest. Designed screening simulation experiments identifies influential factors to provide guidance for tactical employment of Blue Force assets, as well as provide alternative means to influence Red force behavior in a beneficial manner. This thesis analyzed the effects of the influential factors with respect to the percentage of threats interdicted, time to acquire threats, and mean distance away from the FOB that the threats were interdicted. Through analytical techniques, a quantifiable measure of the employment strategy for the UAV and ground-based interceptor was achieved.

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SITUATIONAL AWARENESS FOR SURVEILLANCE AND INTERDICTION OPERATIONS (SASIO): TACTICAL INSTALLATION PROTECTION

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EXECUTIVE SUMMARY

Security of a Forward Operating Base (FOB) is of high interest and operational importance to the U.S. military and allied forces. The Situational Awareness for Surveillance and Interdiction Operations (SASIO) model simulates the operational tasking of a single Unmanned Aerial Vehicle (UAV) and a ground-based interceptor that is designed to search, identify, and intercept potential hostile targets prior to reaching the FOB. This thesis explains the SASIO model and its implementation in JAVA. The goal of this thesis is to provide insight into influential factors that lead to developing the matrix pertaining to the percentage of threats interdicted, time to acquire the threats and distance away from the FOB that the threats were interdicted.

Insights and Recommendations

Utilizing analytic techniques, the thesis explored the employment of Blue Force assets, as well as Blue Force action that is external to their asset employment strategies. The sensor characteristics of the UAV minimally impacted the response variables studied for this scenario. However, the UAV as a surveillance asset did provide the ground-based interceptors an increased detection range allowing for a marginal increase in interdicting the threats.

Utilizing a single UAV and ground-based interceptor, the actions of whether the ground-based interceptor patrolled or remained stationary at the FOB dramatically influenced the percentage of threats interdicted, as well as the mean distance away from the FOB. If the ground-based interceptor patrolled, the percentage of threats interdicted decreased by 53%, while the mean distance away from the FOB for interdiction increased by 11%. Therefore, through analytical techniques, a quantifiable measure of the employment strategy for the ground-based interceptor was achieved.

The most influential factor with respect to all of the responses is the enemy's speed as they traverse towards the FOB. As the speed of the enemy increased, each

response degraded. Therefore, if external checkpoints are provide by indigenous personnel to reduce the enemy's traversal speed, then the Blue Force can more effectively interdict the threat.

Scenario and Concepts of Operations

The probability and stochastic models discussed in this thesis include multiple moving neutral and threat ground objects and a surveillance and interdiction force comprising a single UAV for surveillance and identification and a single ground-based interceptor designed to intercept and clear any hostile objects. Upon initialization of the scenario, the threats and neutral objects arrive in the area of interest randomly and traverse towards the FOB. The goal of the Blue Force is to detect and identify the threats, issue commands to the ground interdictor, and clear the threats prior to reaching the FOB. Once the UAV detects and identifies (with some identification error) the threats, then the interceptor's responsibility is to traverse towards the threat in order to clear that threat.

LIST OF ACRONYMS AND ABBREVIATIONS

AOI	Area of Interest
BDA	Battle Damage Assessment
COP	Common Operational Picture
DES	Discrete Event Simulation
DOE	Design of Experiments
FIFO	First-in, First-out
FOB	Forward Operating Base
GBOSS	Ground Based Operational Surveillance Systems
ISR	Intelligence, Surveillance and Reconnaissance
QRF	Quick Reaction Force
RTB	Return to FOB
SASIO	Situational Awareness for Surveillance and Interdiction Operations
SI	Surveillance and Interdiction
SME	Subject Matter Experts
TTP	Tactics, Techniques and Procedures
UAV	Unmanned Aerial Vehicle
UPM	Uncertain Probability Maps
VBIED	Vehicle-borne Improvised Explosive Device
VV&A	Verify, Validate and Accredit

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I. INTRODUCTION

A. PROBLEM/ NAVY INTEREST

Surveillance and Interdiction (SI) problems are of great interest to the United States military due to the necessity to obtain pertinent information of potential hostile threats and to neutralize those threats upon their correct identification. The military utilizes numerous assets such as, but not limited to: Unmanned Aerial Vehicles (UAVs), Ground Based Operational Surveillance Systems (GBOSS), and satellite imagery to aid in categorizing the entities' actions as threats or not. Upon detection and identification of possible threats, the military must take action to minimize and/or perturb the aforementioned threats to maintain security within the regions of operation. Linking the surveillance and interdiction efforts together is an operational hurdle that must be overcome to ensure the safety of our military forces.

The attack on the USS Cole (United States Department of Defense, 2001) may be classified as an SI problem, and it illustrates the necessity to process relevant information in a rapid manner. Given the atmosphere surrounding this event, proper patrolling of the surrounding waters, as well as inspection of any approaching vessels prior to allowing the vessel to tie up to the ship, may have thwarted this attack. Another attack that falls within this class of problems is the Suicide Vehicle-borne improvised explosive device (VBIED) attacks on an Iraqi Army checkpoint (Multi-National Corps—Iraq, 2008). Quick Reaction Force (QRF) units and checkpoints were established to prevent such an attack; however, the actions by embassy personnel were not able to properly identify and detect the VBIED. The overall problem, as noted above, is the fact that although information and data surrounding an operational environment may be available, the ability to take action to mitigate such attacks requires relatively quick analysis that produces feasible and desired results. In this context, for example, "the true operational art behind that strike [airstrike that killed Zarqawi] was a multidisciplined intelligence, surveillance, and reconnaissance endeavor with agile special operating forces … resulting in a find-fix-finish operation" (Cantrell et al. 2008).

One such instance of the necessity for find-fix-finish operations is for the installation's protection. Suppose the military is operating within the confines of a Forward Operating Base (FOB) within a region. The security of this FOB is paramount due to the military operations that take place in the region. Military scouts, such as UAVs, may be flown for surveillance purposes to allow the FOB to extend its detection and identification range to ensure an adequate standoff distance from any threats that may try to attack and/or infiltrate the base. The data obtained from the UAV can either be automated via tracking and identification algorithms, which allows the UAV to perform its operations without the need of a human to make complex decisions, or employ the current "human-in-the-loop" process, which requires a human to process mass data in either live-feed video or still imagery. Based on the data, the commander must make complex decisions to counteract actions that may be threatening the installation.

The decision to engage an enemy must be made based on quick-turn analysis of surveillance data such that the entity is ideally cleared outside of a predefined standoff distance away from the installation to ensure minimal loss to life and property. Current doctrine requires action on any potential threat; this ensures that all entities are cleared through interdiction. However, following this doctrine, manpower is not utilized in an efficient manner, and if limited resources exist, then clearing all entities may not be possible. This thesis illustrates how the SASIO simulation model can be used as an analysis tool to provide commanders with insight on employment techniques to counter potential threats given limited surveillance and interdiction resources to protect a FOB (or any other location that requires protection).

B. BENEFITS OF STUDY

Surveillance and Interdiction problems appear in many forms. The military is relatively good at gathering the data from surveillance assets, but linking potential flags from one data set to another to obtain a course of action during military operations is relatively slow. During military operations, Combatant Commanders are either not given concise information, which may or may not require immediate action, or they are presented with data requiring actions that ultimately exhaust the assets without

investigating all of the potential threats or options. Understanding and acting on only pertinent intelligence in a timely manner can alleviate exhaustion of assets, as well as minimize the risk associated with performing extraneous interception missions for low-threat targets. This thesis explains the Situational Awareness for Surveillance and Interdiction Operations (SASIO) model and how Combatant Commanders can use this model in support of relevant SI settings. Situational awareness, as defined for this thesis, represents the knowledge and understanding of the environment and the actors within that environment. Use of the SASIO model supports either real-time employment strategies (decision support) or robust design strategies (analysis tool) to maximize the employment of surveillance and interceptor assets. The pertinent intelligence gathered from the employment of such assets could enable more effective interdiction of threats as they may arise or before they engage.

The SASIO model was developed to provide a decision support tool based on currently available and forward-deployed assets. SASIO may utilize current characteristics of surveillance and QRF assets to provide an employment strategy via multiple simulation iterations, as well as provide real-time support through simulation iterations based on the ever-changing theater. The SASIO model can support many classes of SI contexts ranging from the aforementioned FOB protection, border protection, counter drug operations and Maritime operations with regards to anti-pirating operations. These types of problems share common components that comprise any SI missions:

- Utilize surveillance assets to patrol the area to identify threats pertaining to the security of the area of operation
- Detect and classify threats and neutral actors based on the intelligence gathered from the surveillance asset
- Transmit the information obtained by the surveillance asset to interdiction assets
- Interdiction assets can either investigate and/or interdict the actor based on the transmitted report or wait for additional reports

Utilizing this framework, while combining the effects of probabilistic sensing and motion by Blue Force assets, the evolution of this model can provide Commanders with a

decision support tool. SASIO links the gathering of information to the execution of actions that must be performed to ensure security of an area through recommendations and potential outcomes of a failed action.

In support of such a tool, SASIO provides insight into the factors of relevance for performing said tasks, such as: speed of each asset (UAV, QRF), sensor characteristics (false positive and missed detection) rates, when the QRF takes action and also aid in determining a secure location for a FOB within a hostile region. SASIO may be iterated through with varying factors relatively quickly, which could allow an analyst to provide asset employment recommendations based on the current operational environment being studied. Combining this fact and performing sensitivity analysis on these factors, the potential shortcomings of current technology and doctrine (e.g., Tactics, Techniques and Procedures) may be evaluated to provide meaningful insight in the context of SI problems, and revised as necessary.

This thesis makes use of the SASIO model to explore the effectiveness of a single UAV and a single QRF with regards to the protection of a FOB. Numerous factors are examined in order to analyze their significance in the proper employment of these forces to combat a potential threat to the FOB. This threat is characterized as a vehicle-borne improvised explosive devise that can damage the FOB even if the threat does not reach the FOB. As the distance from the FOB to the interdicted threat is increased, then the destructive capability of the threat is decreased. The scenario makes use of the topographical constraints and road network found at Camp Roberts Army National Guard installation in California.

This work is motivated by ongoing field experimentation efforts via the Naval Postgraduate School and the United States Special Operations Command (USSOCOM) Field Experimentation Cooperative program (Bordetsky et al., 2009). The current experimental scenario includes a forward-deployed, 12-man team designed to protect their command installation (Special Operations team house) while performing intelligence, surveillance and reconnaissance (ISR) operations via UAV assets. Through use of limited resources, primarily minimal surveillance assets, employment tactics for the UAV based on varying theater configurations (SOF team house placements) are

evaluated. Based on time constraints (e.g., long lead time required to perform a single live experiment), the SASIO model can be used in conjunction with current field experiments to provide analysis based on current tactics utilized, as well as provide insight into alternative employment strategies to maximize the protection of an installation.

The SASIO simulation engine incorporates a modular type framework. The user may select any currently built-in motion or interdiction models, or may create their own to test out new employment techniques for both the surveillance and interdiction assets alike. This feature is useful given that an employment for one theater may not be efficient or appropriate for another. This modularity ensures that the user is not limited to a single technique, but is able to evaluate a multitude of strategies to combat an evolving enemy.

C. RELATED WORK

There have been recent research efforts with respect to the employment of UAVs for ISR type missions. Prior to performing ISR tasks, the underlying class of problem must be understood. Mission planning and employment must take into account aspects of classical search modeling as it applies to the imperfect sensor characteristics of the UAV. Washburn (2002) studied the propagation of errors in a simulation due to an imperfect sensor. Berner (2004) studied sensor characteristic of varying UAVs to obtain situational awareness for protection of a high value target while Raffetto (2004) focused primarily on the factors of airspeed and loiter times for the UAV. Berner’s (2004) study analyzed how a broad area search UAV with imperfect sensor characteristics may be used in conjunction with a better detection and identification UAV with a relatively lower detection range to increase the coverage surrounding a particular mission region.

Once situational awareness is achieved for a region, the ability to allocate a QRF and proper employment of alternate surveillance assets must be performed to acquire targets within a short time after identification. Chung et al. (2009) formulated a Mixed-Integer program utilizing Bayesian updates to perform the task of allocating surveillance and QRF assets to rapidly identify potential targets. Similarly, this thesis focuses on the tactical uses for each asset. Other methods to rapidly interdict potential targets utilize a

Subject Matter Expert (SME) to manually interject proposed enemy trajectories based on experience in the region. Kress et al. (2007) demonstrated significant improvements in search performance through the implementation of a “two-stage stochastic Integer Linear program” in conjunction with SME inputs. Although this is an interesting improvement to the SI class of problems (consisting of an increase in 50% detection opportunities based on a preplanned generated UAV routing provided by the SME), the paper does not address variations in factors as they pertain to surveillance, such as: sensor characteristics, sensor footprint, sensor loiter time and platform speed. SASIO seeks to investigate such factors, as well as others, to obtain a more robust design for coordinated employment of each type of agent.

Much of the past research has focused on the surveillance abilities of the UAVs. Upon a UAV observation, the UAV transmit the location of the threat to the QRF with some time delay due to transmittal distance. With this time delay, an error in the exact location of the threat arises and the location must be offset to account for this error to provide a successful interdiction. Bertuccelli et al. (2006) illustrated the importance of taking into account variability in information due to time delays for UAV search and ground interceptions. The author used Uncertain Probability Maps (UPMs), which accounted for poor knowledge and propagations of the target location throughout the environment. Through recursive calls of a distribution of the targets’ trajectories, the maps are generated and updated for efficient search. In this thesis, UAV routes are heuristics based on a probability map representation of situational awareness that is updated with real time observations.

For the purposes of this thesis, SASIO performs the tasks of SI based on a single UAV for surveillance and a single QRF. Other past works have studied the case where multiple assets were utilized. Yan et al. showed UAV performance of multiple tasks based on their capabilities such as: searching, confirming, attacking, and performing Battle Damage Assessment (BDA) (Yan et al., 2003). The authors used deterministic Discrete Event Simulation (DES), continuing efforts until all targets were eradicated. This model illustrated that there exists a point in which an increase in the number of UAVs showed diminishing returns. Also, an active search algorithm for the UAVs was

more effective than a random search in eradication of targets. In contrast, the SASIO project utilizes a time-stepped simulation, integrate imperfect observations with Bayesian updates, and vary numerous factors pertaining to Red and Blue Force assets and theater.

D. THESIS ORGANIZATION

The main contributions of this thesis are the development of the SASIO model as well as the analysis and resulting insights for tactical employment of Blue Force assets in an SI context. Chapter II outlines the basic elements used in constructing the SASIO model. In Chapter III, the thesis delves into the details of the model while highlighting potential variations in the model to explore alternate scenarios. Chapter IV discusses the scenario analysis and presents the reader with the results of the analysis, as well as the operational and tactical insights that may be obtained from the analysis. Chapter V provides a summary of this research and the conclusions as well as present avenues for future research.

E. SCENARIO

Within the area of interest (AOI), the military has created a FOB where military operations for the immediate region based. There are three roads that we consider three entities entering this area, one of which is a threat, while the other two are neutral. Each entity enters the AOI and traverses the road toward the FOB at a constant speed.

The assets in place to protect the FOB (Blue Force) consist of a single UAV for surveillance and a single QRF to interdict and clear the threat. The UAV performs surveillance along fixed radii paths from the FOB. The purpose of the UAV is to give the Blue Force the ability to identify a threat while at an increased standoff distance from the FOB. Upon a detection and identification, the UAV issues a report for the QRF to interdict the threat.

The QRF performs a patrol surrounding the FOB at a distance of 250 m along the road network. The QRF has the ability to perform surveillance, as the patrol is occurring and interdict threats that are within this surveillance range. Therefore, the QRF provides a second line of defense to the FOB.

F. ASSUMPTIONS

Theater

Road Network – The road network is a directed graph from entry nodes to the AOI towards the FOB.

Node Separation – Each node is 250 m apart.

Theater Map - Each node has a probability of a threat in that node and continues to be updated as observations are made by the Blue Force assets via a Bayesian updating process.

Objects

Expected Arrival Time – The objects have a minimum inter-arrival time of one unit.

Traversal Speed – Threats and neutrals traverse at a fixed speed (unknown to the Blue Force).

Traversal Direction – All objects traverse towards the FOB.

Agents (UAV)

Surveillance Path – The UAV flies a fixed waypoint paths at varying distances from the FOB.

Detection/Identification – The UAV has perfect detection and imperfect identification.

Report Issue – The UAV issues a report upon (possibly erroneous) positive threat identification.

Agents (QRF)

Patrol – The QRF performs a patrol of either a single node waypoint path away from the FOB or remains stationary at the FOB.

Clearing – Upon interdiction of a threat, the QRF detains the threat and clear the threat after the appropriate time has elapsed.

Visible Cells – The Blue interdiction force has the ability to perform surveillance within its current cell as well as adjacent cells based on the users input.

Detection/Identification – The QRF has perfect detection and identification

II. MODEL FORMULATION

A. OVERVIEW

This chapter describes the development of the theater, scenario and taskforce. The theater governs the region in which the entities interact. For this thesis, the theater is specified as a region patterned after Camp Roberts Army National Guard facility in California. The scenario is synonymous with the objects not characterized as Blue Force. These objects may be categorized in the form of neutral or threat objects. The last portion of the model is the taskforce entities, which includes all Blue Force assets, surveillance and QRF alike.

B. DESCRIPTION OF THEATER

The AOI for this scenario is at Camp Roberts, and was chosen due to the ability to utilize aerial and ground based assets to calibrate the model. The chosen roads form a "Y" shaped network with the FOB located where the three roads intersect. Each road is discretized into nodes separated 250 meters apart from each other and the labeling of the nodes is arbitrary, though once labeled, each node is maintained and known to all Blue Force entities within the simulation representing a common operational picture (COP). The scenario theater is depicted in Figure 1.

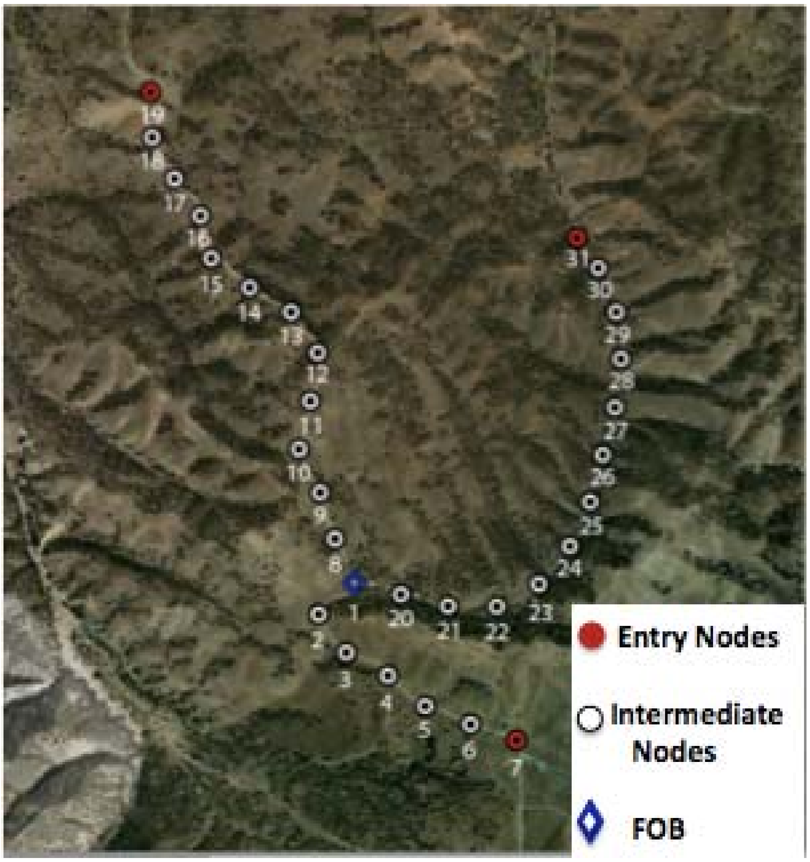

Figure 1: Camp Roberts, CA: FOB located in center and depicted with blue diamond. Entry nodes are illustrated as red circles, while intermediate nodes are in white. Each node is separated in 250-meter increments.

The graph representing the road network is an undirected graph linking each node to the adjacent nodes. This allows for objects, Red and Blue ground elements alike, to transit throughout the area by moving from a single node to its adjacent node. The southern road has only 1.5 km in total distance from entrance to the protected FOB location, while the other northern routes are 3 km in total distance. This was determined based on airspace constraints within Camp Roberts. The separation of 250 m from one node to the next was chosen due to the nominal sensor footprint of the aerial asset utilized. In other words, the asset, while flying at its nominal altitude, provides a 250 m wide footprint, thus allowing thorough observation of a single node during each pass.

C. DESCRIPTION OF SCENARIO

1. Arrival Model of Vehicles

Both neutral and target type vehicles enter the road network via the entry nodes and travel towards the FOB. Assume that any object traversing the network away from the FOB pose no threat to the installation and can be disregarded. Each object's arrival is assumed independent and the rate associated with their inter-arrival times to begin their transit down a road is denoted by parameter rate λ (an event per unit time). Consider time to be discretized in Δt increments, utilizing the underlying properties of the geometric distribution as the arrival process; the probability that the target arrives at time t is $\lambda\Delta t$. Each arrival is independent from the other and memoryless due to the geometric distribution.

Suppose that the total number of vehicles, N, will not exceed three vehicles on the road network; thus, $N = 3$. This can be assumed due to a coordinated checkpoint system in the road network to ensure that the network is not overwhelmed with traffic. The scenario evaluates the arrival of the objects under three distinct instances of inter-arrival rate: λ_1, λ_2, λ_3 where $1 = \lambda_1 < \lambda_2 < \lambda_3$.

When stating that the arrival of objects has a one-time step inter-arrival time, this simply states that objects arrive with one time unit separation. The investigation of Blue's ability to properly interdict the target while observing all objects, threat and neutral alike, is a difficult task. Analyzing the one inter-arrival instance provides a worse case basis against which all later scenarios may be evaluated. Then the thesis will explore the best Blue Force case with a large inter-arrival time.

An Intermediate inter-arrival time (λ_2) is simulated to ensure that nominal traffic patterns are explored. Through simulation and analysis, this inter-arrival time provides insight into a more realistic scenario setting, since the objects will not be all arriving at a single time, nor arriving in such a manner that only a single object is in the scenario during any given time.

The largest inter-arrival time (λ_3) utilized for this thesis is setting the inter-arrival time to the time required to traverse the longest road by any single object. Under this rule, the simulation may be thought of as only exploring a single object's motion from the entry into the theater to the destination at any given time. Since there is only a single object to be identified and interdicted, an upper bound with respect to the Blue Forces' ability to perform its operations will be analyzed.

2. Random Selection of Roads

Given the arrival rate of vehicles to the road network, the avenue of approach, i.e., the road traversed by each vehicle, is also assumed a random component of the scenario. The theater consists of three roads that lead to the FOB location. The three roads have a distinct entrance node for the enemy to begin its transit. Supposing that there exist three objects, one being a true target, the initialization of where the objects begin may be simulated in the following ways:

- The objects begin on each of the three roads, such that each road contains only one object
- The choice of roads is independent from object to object

The first proposed concept for object placement is realized by drawing a random number based on the number of roads that exist. Once the number is drawn, the road is assigned to an object and is then discarded from the possible choices of roads. This process is repeated until all roads have been assigned to the objects. For example, consider the Camp Roberts' network where entry nodes are labeled 7, 19, 31, as shown in Figure 1. Utilizing the idea of assigning a road to an object and then discarding that road as a possible choice ensures that the roads are not duplicated from object to object.

$$R \sim U(0, N);\ \text{where } N \text{ is number of entry nodes}$$

Next iteration:

$$R \sim U(0, N-1);\ \text{where } N \text{ is number of entry nodes}$$

The second concept allows each object access to all of the entry nodes as their initial starting location. A random number is drawn from the list of possible starting locations. Based on the random number, the node is chosen and then assigned to an object. The iteration of this process is continued until all objects have an assigned entry node.

$$R \sim U(0, N);\ \text{where } N \text{ is number of entry nodes}$$

The former method of road selection by the objects depends on the objects that have already arrived. This dependence simplifies the scenario because once an object has been observed on a single road and interdicted, then that road would not need to be observed again. Although this is an assumption of the arrival process, the simulation does not account for this dependence and continues to search for objects regardless of whether an object was found on a single road or not.

The road selection method that allows for multiple objects to arrive on a single road is independent from one road selection to the next. This type of problem is more complex for interdiction operations due to the fact that objects may arrive on the same roads shortly after other prior arrivals. Therefore, if an observation is made and the surveillance asset continues on to the next road, the remaining objects may traverse the road undetected by the surveillance asset. Thus, the only chance that the object is interdicted prior to reaching the FOB rests with the surveillance capabilities of the QRF. Supposing that the QRF does not have the ability to look out past the current location and the QRF is not performing a patrol, then all the objects that leak through the surveillance asset will reach the FOB. Comparison of these two approaches highlights any advantage of considering the more difficult independent case. Modeling the interdiction failure and the percentage of objects that reach the FOB under this premise provides insight into operational tactics and utilization of the surveillance and interdiction assets.

3. Object Motion Model

When developing the SASIO model, the discrete time step used to measure the progression of entities represents an arbitrary unit of time. The time step utilized

throughout the model is scaled in such a way that all objects, neutral or threat, are assumed to not traverse more than a single cell in a given unit of time. This allows for an observation to be made in any given cell such that the object is either present or not due to motion through the cell and not by “jumping over” a cell. This assumption is relevant and is utilized when the surveillance and QRF assets perform observations which later feed into an updated probability map which illustrate the probabilities of where an object is within the theater.

Assume that each vehicle approaches the FOB with a constant, deterministic speed, denoted by ν. For the discretized road network, the vehicles’ speeds are converted from a continuous velocity to that which is discrete which corresponds to the number of cells traversed in a given time step. For example, $\nu = 1$ corresponds to a traversal of one nodes in a single time step, where as $\nu = 0.25$ is analogous to a slower vehicle requiring four time steps to transit to an adjacent node. Upon starting the simulation, the objects speeds are set to one of the following: 1 (the objects move every time step), 2 (the objects move in two time steps, i.e., $\nu = 0.50$), and 3 (three time steps to move, i.e., $\nu = 0.33$). The justification for modeling object movement in this way follows.

Given the theater is constructed so all object traffic tends to flow from an entry node towards the FOB, a directed graph may be constructed based on the adjacency list of the theater. The pseudo code in Figure 2 represents the object motion model for the objects. From this implementation, a visual representation of the motion model, as in Figure 3, illustrates the pseudo code execution of an object moving in 3 time steps, as it pertains to the Camp Roberts’ scenario.

Algorithm 1: Object Motion Model

Input:	Directed graph from Theater
	Object's speed
Output:	Object's next location

INITIALIZE:

```
-Directed Graph,
      G'
-Set Counter = Object speed
```

Algorithm

```
While(true)
      -Decrement Counter
      If(Counter == 0)
         -Determine adjacent node
         -Transit
         -Reset Counter to Object's speed
      End
End
```

Figure 2: Pseudo code representing Object Motion Model implementation

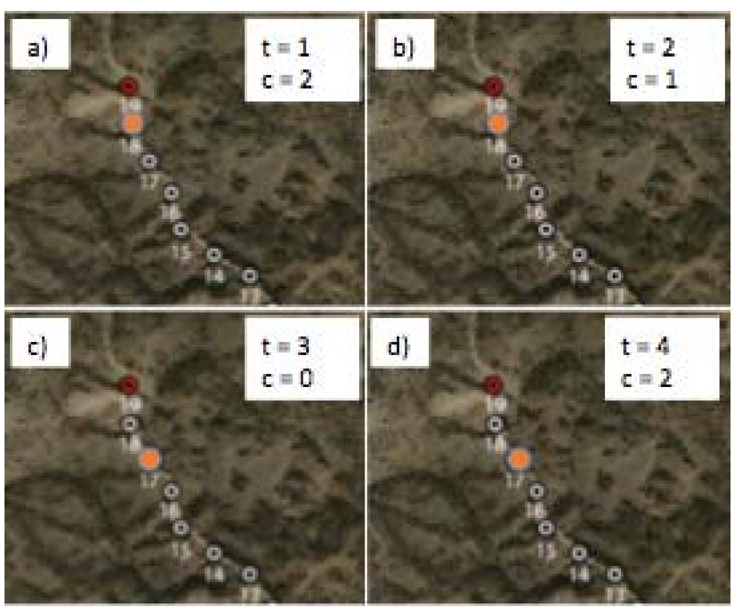

Figure 3: Object motion model implementation for an object that traverses from node to node in three time steps

The above models pertain to the objects defined in the scenario. Future studies may investigate more sophisticated constructions facilitated by the modular design of the SASIO framework.

D. DESCRIPTION OF THE TASK FORCE

1. Platform

a. Surveillance Asset: Unmanned Aerial Vehicle

The Unmanned Aerial Vehicle (UAV) performs surveillance operations as dictated by the operator. For this scenario, the UAV performs a patrol pattern of given radius from the FOB. Based on its operating speed, the UAV flies each node in its given waypoint list, performing observations and identifications upon arrival to a node, loitering briefly, and continuing its patrol route. Such a pattern can be easily accommodated by current waypoint-based UAV auto-pilot, enabling operators to focus on examining down linked imagery.

b. Interdiction Asset: Quick Reaction Force

The Quick Reaction Force is a mounted vehicle asset whose primary role is the security of the FOB. This asset performs surveillance through patrol routes, as well as interdict potential threats that are obtained from the surveillance asset. While performing patrols, the QRF performs a predefined patrol pattern until the surveillance asset makes an interdiction request. The QRF transitions to an interdict mode and services the request by traversing towards the location where the request originated. Once an interdiction is made, the QRF clears the object and then returns back to the FOB to continue its patrol. This process of patrolling, interdicting and returning back to patrolling provides protection for the FOB through surveillance and interdicts the threat while maintaining a standoff range from the FOB.

2. Probabilistic Modeling of Situational Awareness

a. Probability Maps

The SASIO simulation utilizes a dynamic probability map to govern a actions by the QRF. A probability map, as defined in the context of this thesis, is an array of probabilities for each node within the theater, which allows the user to perceive the likelihoods of where an enemy may be located. The user initializes the simulation with what is believed to be the location of the threat or the probability that the threat may traverse a given set of node based on intelligence gathered for the area.

The probability map representation used in this thesis is an important aspect of SI problems. The probability map's primary function is to resolve whether a query and/or interdiction of an object must occur by the QRF. The QRF may be performing surveillance operations in conjunction with the UAV; however, once the Commander deems that there is a threat object along a road with high confidence, then the QRF transitions to the interdiction mode to pursue such a threat. This transition directly relies on the probability map rapidly evolving as observations are made by the UAV. If no intelligence is obtained for the AOI, then the user can define a uniform probability along the entire theater as follows

Let X $\in \{1, 2, .., C\}$ be defined as a RV of the location of the object

where C is the number max number of nodes in the theater

$\rightarrow \mathrm{P}[\mathrm{X}_c] =$ probability that a threat is located in cell C

$$P[X_c] \sim U(0,1) = \mathrm{P}[\mathrm{X}_c] = \frac{1}{C}$$

As the simulation progresses and the surveillance asset makes observations, the probability map is updated based on these observations according to the observation models described in the following section. Suppose that the surveillance asset performs an observation in cell five and the surveillance asset does not observe a threat, then the probability that a threat is in cell five is decreased for the probability map. The converse is also true. The way in which the probability map incorporates imperfect observations is through a Bayesian update.

b. Bayesian Updating

Each node is updated independent from the other cells. Therefore, if an observation is made in one cell, then that cell alone will be updated. Using this method to update the cells is used over a joint cell updating because as more UAVs are used, the updating process becomes more difficult. Given that the cells' identifications are imperfect, the single cell updating is more plausible because after an observation and identification is taken, then only that cell should be updated.

The detection process for the UAV relies its sensor characteristics. Assuming that the UAV is equipped with perfect detection sensors, and the simulation was run holding all other parameters constant, then the result of this simulation run would be the best-case scenario. Suppose that the UAV is performing surveillance in accordance with a user-defined route. As the UAV observes a cell, the UAV processes whether an object is present or not with 100 percent confidence due to the perfect sensor suite. Therefore only a single "look" is required to verify if an object is present or not. Once an object is identified in the cell, then the classification of whether that object is a target or neutral must occur. Therefore, if the UAV could detect and classify the objects in the AOI with perfect confidence, then an upper bound on the problem is defined assuming that all other parameters are held constant from an execution of the simulation to the next. Since technological advance have not been made to create the "perfect-sensor package," this thesis explores Bayesian updating of the probability map to classify objects entering into the AOI given an imperfect sensor package.

(1). Detection. The SASIO simulation models the detection process made by the surveillance and interdiction assets as a perfect sensor. Therefore, if either asset observes an object in the cell that surveillance is being performed, then the asset detects that object. The SASIO framework does allow for imperfect detection, but for the purposes of this scenario, perfect detection is modeled.

The basis for the perfect sensor for the UAV and QRF is due to the verification runs that were performed at Camp Roberts in August of 2009. Utilizing a UAV for surveillance and observing the live-feed broadcasted back to the user, detection

of an object was easily achieved by the operator. Therefore, the process of perfect detection was modeled in the SASIO simulation.

(2). Identification. Since imperfect identification is modeled in the SASIO simulation, some meaning of an imperfect sensor must be understood. There are essentially four different cases for probability of identification that may occur when an observation is performed. Prior to stating the four cases, some nomenclature for this derivation must be defined.

Assume that a positive detection occurs in cell c; otherwise, no identification takes place

Let Z_c be a Bernoulli random variable describing the true identity as defined below

$$Z_c \triangleq \left\{ \begin{array}{ll} 0, & \text{object type is a neutral} \\ 1, & \text{object type is a threat} \end{array} \right\}$$

Let W_c be a Bernoulli random variable describing the observation, as defined below

$$W_c \triangleq \left\{ \begin{array}{ll} 0, & \text{observation "says" object is a neutral} \\ 1, & \text{observation "says" object is a threat} \end{array} \right\}$$

There are four distinct cases that an identification can take on: the probability of a correct negative identification “1-γ” (eqn. 2.1) (correctly observing no threat present), the probability of a false positive detection “γ” (eqn. 2.2) (saying the object is a threat when its not), the probability of a missed detection “ρ” (eqn. 2.3) (saying the object is a neutral when it is a threat), and finally the probability of a correctly identifying a threat “1-ρ” (eqn. 2.4).

Let $Z_c = 0$ represent an object of type neutral is detected in cell c

$W_c = 0$ represent an identification "says" object is a neutral in cell c

$$P(W_c = 0 \mid Z_c = 0) \triangleq 1 - \gamma \qquad \text{(eqn. 2.1)}$$

$W_c = 1$ represent an identification "says" object is a threat in cell c

$$P(W_c = 1 \mid Z_c = 0) \triangleq \gamma \qquad \text{(eqn. 2.2)}$$

Let $Z_c = 1$ represent an object of type threat is detected in cell c

$W_c = 0$ represent an identification "says" object is a neutral in cell c

$$P(W_c = 0 \mid Z_c = 1) \triangleq \rho \qquad \text{(eqn. 2.3)}$$

$W_c = 1$ represent an identification "says" object is a threat in cell c

$$P(W_c = 1 \mid Z_c = 1) \triangleq 1 - \rho \qquad \text{(eqn. 2.4)}$$

So, now that identification can be made utilizing an imperfect sensor, the probability of an object being a threat based on prior knowledge of that location must be also taken into account. Using this method of prior knowledge of the threat location in conjunction with observations being made by the surveillance asset will either increase the probability that a threat is in the observed cell or decrease that probability.

SASIO assumes an independent cell Bayesian update. This method assumes that given an observation in a single cell; the probability in that cell alone will either increase or decrease based on that observation. Other methods could be utilized, such as an update method, considering the joint distribution in which e.g., a positive observation in a single cell is made, then the probability that the object in the other cells decrease. This method becomes more complex if more than a single object exists in the AOI.

The process of taking observations and updating the probability of where an object is located is an iterative process. Thus, the prior probability is continually updated as observations are performed. This updating is through utilizing Bayes rule (eqn. 2.5)

$$\mathrm{P}[Z_c = z \mid W_c = w] = \frac{P[W_c = w \mid Z_c = z] * P[Z_c = 1]}{P[W_c = w]} \qquad \text{(eqn. 2.5)}$$

The left hand side is the posterior probability that an object is a threat or neutral given that an observation occurs in cell *c*. Since in the presented model, we utilize the independent cell-updating rule, updating any cell other than the cell that observation is being taken in does not need to be performed. This decoupling allows for efficient computations, linear in the number of observations vice number of cells. On the right hand side of the equation, the numerator represents the probability of an observation multiplied by the prior belief of the location of the target. The denominator is the marginal probability of all observations. As an example, suppose that the threat is observed in cell *c* and that the object is a threat (i.e., $Z_c=1 \mid W_c = 1$). Then the following result for cell *c* in the probability map occurs:

$$\mathrm{P}[Z_c = 1 \mid W_c = 1] = \frac{P[W_c = 1 \mid Z_c = 1]] * P[Z_c = 1]}{P[W_c = 1 \mid Z_c = 1] * P[Z_c = 1] \;+\; P[W_c = 1 \mid Z_c = 0] * (1 - P[Z_c = 1])} \qquad \text{(eqn. 2.6)}$$

Substituting eqn. 2.4 for the numerator and expanding the denominator is as follows:

$$\mathrm{P}[Z_c = 1 \mid W_c = 1] = \frac{(1-\rho) * P[Z_c = 1]}{(1-\rho) * P[Z_c = 1] \;+\; \gamma * (1 - P[Z_c = 1])} \qquad \text{(eqn. 2.7)}$$

This iterative process occurs with each observation by the UAV. As the UAV performs more and more observation, the probability in that cell continues to change. Supposing that the UAV contains a perfect sensor package, γ and ρ are equal to zero, that is, no errors in identification, then the equation simplifies to the following:

$$P[Z_c = 1 \mid W_c = 1] = \frac{(1)\bullet\text{prior probability in cell c}}{(1)\bullet\text{prior probability} + 0\bullet(1 - \text{prior probability in cell c})} = 1 \qquad \text{(eqn. 2.8)}$$

Therefore, if there were an ability to create a "perfect sensor," then only a single positive identification would be needed to locate the object. However, the costs to create an almost perfect sensor may be so extreme that utilizing more surveillance assets to obtain more observations may be more effective. Understanding the effect of improving sensors and the implied tradeoffs requires a sensitivity analysis, which this thesis aims to provide.

c. Observation Modeling for the Quick Reaction Force

The QRF can perform observations the same manner as the surveillance asset. If the QRF has the ability to observe nodes that are adjacent to its current location, then observations may be performed on these locations. This may be thought of as the QRF having a person peering through binoculars as the driver transits the patrol route. The lookout may see a single node away (250 m based on the theater) or multiple nodes away depending on the line of sight and focal range of the binoculars.

SASIO takes advantage of a lookout when the QRF is in a search mode. However, the difference between the QRF and the UAV asset is there are no detection and identification errors associated with the QRF, while the UAV has identification errors. Thus, Bayesian updating updates the probability map based on the UAV's observations and aids the QRF as a decision-support tool dictating when an interdiction must be performed.

d. Report List Generation

The data obtained from observations that result in a positive identification must be relayed to the Commander for review and/or action. This information is transmitted in a report list format. A report list is a list of all reports made by the surveillance asset. The report includes pertinent information regarding the observation such as: the time that the observation occurred, the location of the observation, which surveillance asset made the report and any description of the suspected target. As with a

real SI operation in which observations and reports are sent to the Commander, this report list process is emulated in the simulation. Action to either interdict or query the objects on the report list represents a Commander sending out a QRF to investigate a potential threat. SASIO uses the report list as a tool to transition the QRF from a searching phase to an interdiction phase and may do so once the report is obtained. Once the report is cleared by the QRF, the report is removed from the list. Current SASIO model implementation services the reports in a First-in, First-out (FIFO) type queue.

3. Trajectory Modeling

a. Unmanned Aerial Vehicle

The UAV's patrol path is not geographically constrained since its flight path is not limited (other than by airspace restrictions) for this scenario. Therefore, the flight paths that will be investigated within this thesis will be of varying radii of 250 m, 500 m, and 1000 m away from the FOB. Varying the radius of the flight path can either aid the Commander in interdicting threats by detecting and observing the objects at a longer range; however, it may also hinder the operations due to the increased leg distances from one waypoint to the next.

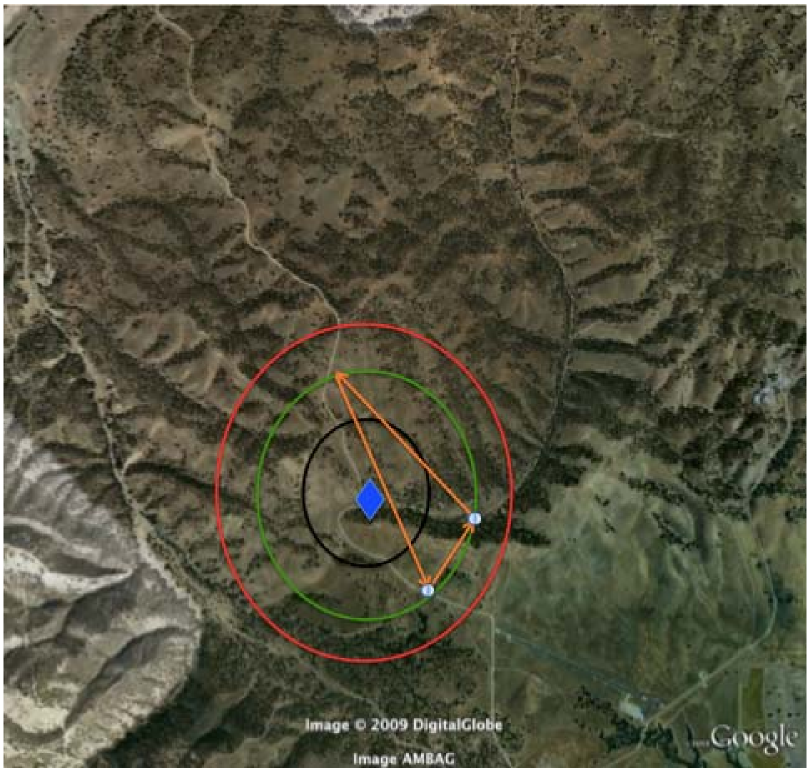

Figure 4: Varying radii flight paths for the UAV with predefined flight profile (orange) based on 750 m radius from the FOB

Let *WP* be a list of waypoints that are desired for surveillance operations. Each waypoint distance is calculated based on Latitude and Longitude coordinates from the current node to the next node in the list. Assuming that the UAV flies at a calibrated speed of ν = 450 m/min which is equivalent to 15 knots, the UAV reaches the next node in the list when the allotted time to traverse to the next cell is met.

WP = {1, 2, 3, 4}

Let UAV[0] $\in$ WP be defined as the current cell of the UAV

Let UAV[1] $\in$ WP be defined as the next node in the list of WP

$$\text{Time to next WP} = \frac{Dist(UAV[1]) - Dist(UAV[0]}{v}$$

Upon the UAV's arrival to a node, the UAV performs surveillance operations as described previously. Upon completion of the observation, the UAV continues on to its next location. The user may desire the UAV loiters at each location for

a desired time prior to moving on to the next location. SASIO model implementation may take this into account to allow for a longer "look" at each node in question. Follow-on studies to this thesis may incorporate a dynamic flight profile in which the UAV loiters at a location only if detection is made. This allows for additional processing time to discern the detection as either a threat or neutral. The next layer of difficulty would include allowing a dynamic flight profile for the UAV such that if an object is detected along the road, the UAV continues to track this object until a QRF asset can query the object. Once the QRF reaches the object, the UAV continues on with the predefined patrol path.

b. Quick Reaction Force

(1) Patrolling methods. There are some interesting methods of patrolling that SASIO can implement. Due to the modularity of the simulation model, the user can define two distinct types of patrols performed by the QRF. Stationary or trajectory-based patrols currently exist and each is analyzed in order to provide tactical insight to Commanders on strengths and weaknesses of implementing one method over another. The QRF patrols the AOI when the report list is empty. The SASIO simulation studies two distinct cases of patrol that are currently implemented, stationary and a trajectory patrol based on a specific range from the FOB.

Suppose that a stationary patrol is implemented and the QRF does not have the ability to perform observations outside its current location, then the only line of defense for protection of the FOB relies on the UAV alone. If the UAV fails to detect and identify the threat then the object reaches the FOB unchecked by the QRF. Thus, the QRF must be enhanced with the ability to scout the area surrounding the FOB in order to provide a second line of defense for SI operations.

The second method, trajectory based, is a patrol by the QRF in its truest sense. Figure 5 illustrates a trajectory patrol of the QRF 750 m away from the FOB. The result of performing a patrol under this context may provide undesirable consequences that are counter intuitive initially. Suppose that the QRF is performing a patrol on the southern leg of the theater, there is a chance that the threat is driving down one of the other roads during this time. Based on this instance, the FOB remains

vulnerable to an attack. However, if the QRF is patrolling the leg by which the threat is coming, then the QRF performs the interdiction and thwart any attack prior to the threat ever reaching the FOB.

Figure 5: Illustration of a patrol of one nodes out for the QRF

The final aspect of the SASIO model is the operation of the QRF during an interdiction operation. SASIO implements a Return To FOB (RTB) method that utilizes Dijkstra's algorithm in order to direct the QRF to the FOB. Dijkstra's algorithm is utilized to allow for more complex scenarios. The rational for implementing a RTB operation is to emulate the actions that a Commander would expect following

interdicting a potential threat rather then continuing on with the patrol. This allows for a reset of forces to counteract other threats that are unknown in the area.

(2) Service time for identification of an object. The QRF performs the interdiction of potential threats that were either relayed via the reports obtained from the UAV, or by visual detection of these threats by scouting techniques. The goal of the QRF is to query and/or interdict the objects at a distance away from the FOB in hopes to minimize the number of casualties that would occur in the event that the VBIED reached its goal. Since the QRF is a manned asset, the ability to identify and service the threats upon a successful interdiction requires time, which is a factor that can be varied based on user input.

The service time for proper identification is what may be varied to simulate true interdiction operations. Current implementation allows for this service time to be varied in constant time increments from run to run. This parameter provides insight into the interdiction operations and an upper limit on the service time to ensure that the FOB remains unharmed. By setting the service time to instantaneous, time to service equal zero, an upper bound on the number of objects interdicted can be proposed. Future revisions of the SASIO model may incorporate a queuing model implementation resulting in a nondeterministic service time.

4. Prediction Model

Gathering intelligence with respect to the AOI is one of the most vital actions that must be performed immediately by the Commander and his personnel. The SASIO model implements intelligence gathered for an AOI in the form of a prediction model. This prediction model focuses on the motion of the enemy force to include trajectories and speed at which each object moves. This prediction model takes the form of four different Markov transition matrices depending on the accuracy of the intelligence gathered. Since this scenario ensures that all objects travel from an entry node towards the FOB, a directed graph is used to represent the trajectories. However, the speed at which the objects travel is unknown to the Blue Force. There are three different speeds at which the

objects can travel as described under Object Motion Model: 1, 2, and 3 and from these speeds, the Blue Force may predict the object's next location. Figure 7 below depicts how the object moves from one node to another.

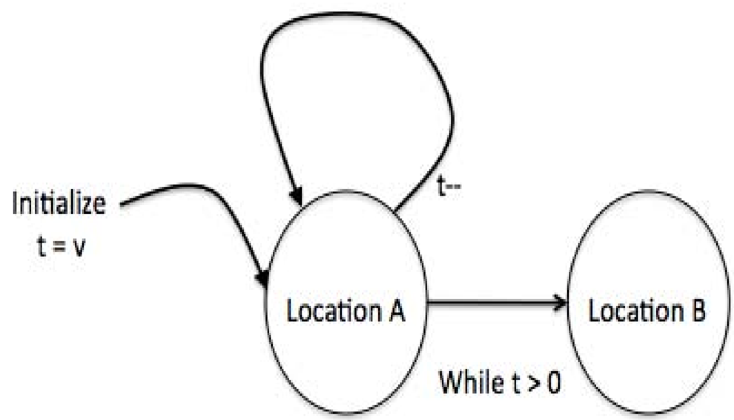

Figure 6: Event graph depicting the Object's motion

Since the Blue Force intelligence includes the trajectories and the object's speed, then if the Blue Force had tracked the object upon entering the area since the object's motion can be predicted given its current location and speed. However, the UAV is the only surveillance asset that the Blue Force has to make observations and the UAV does not loiter at the entry nodes; thus, a prediction of where the object is going to be next must be made since each observation is a glimpse of a single time. Suppose that the object travels every three time steps, and the UAV observes the object, the observation could have been made when the object got to that position, or after the object has been there for one or two time steps. Since the UAV takes the observation and continues on, a report stating that the object is in location X, but the time that the object has been there cannot be determined. Therefore, using this example, there is a $^2/_3$ chance that the object stays in that location while only a $^1/_3$ chance the object will move. An example of the prediction model for the given example is represented in Figure 7.

	To From	1	2	3	.	.	.	7	8	.	.	.	19	20	.	.	.	31
FOB	1	1																
	2	1/3	2/3				0											
	3		1/3	2/3														
	.			.	.					.	.	.	.	.	.	.	.	.
	.				.	.												
	.		0			.	.											
	7						1/3	2/3										
	8	1/3						1/3	2/3									
	.				.					.								
	.				.					.	.							
	.				.						.	.						
	19				.							.	.					
	20				.								.	.				
	.				.									.	.			
	.				.										.	.		
	.				.											.	.	
	31				.												.	.

Figure 7: Prediction Markov transition matrix based on an object transitioning from one node to the next adjacent node in three time steps. Recall that node one represents the FOB node

SASIO predicts the motion of the objects by drawing a random number, and if that number is less than the probability that the object moves, then the prediction states that the object stays in that location. This is iterated each time step, adding each random number to itself, until the object is predicted to move. Therefore, if a prediction model is based off of intelligence depicting the objects to move every four-time steps, but in reality the objects travel every time step, then the objects arrives at the FOB quicker then expected and the Blue Force may not interdict the enemy in time.

Therefore, the parameter of how well the intelligence matches the object's true motion is examined. Through these variations, insight can be gained into the type of intelligence obtained and the importance of the quality of that information.

5. Experimental Design

The SASIO model can be used to study the effect of many factors on the response variables of interest. Experimental design can be used to efficiently explore the design space by simultaneously varying the input factors, which can be analyzed by the user through the graphical user interface (GUI) built for the SASIO framework.

The response variables that are explored in this thesis are: number of threat objects interdicted, time to interdict all threats, and the distance the threats are interdicted

with respect to the FOB. Factor screening is performed first in order to reduce the dimensionality of the design space after which an analysis on the remaining factors carried out.

a. Factors, Levels and Justification

The factors and levels, which are investigated in this thesis, are illustrated in Figure 8. Each factor is a unique characteristic of the entities in the simulation and each level tries to encapsulate the factors that can change during military operations that utilize a UAV for surveillance. Through varying the objects and entities, the model can provide insight regarding employment tactics to overcome the scenario threats. The objects may be varied as follows:

Entities	Type of Variables	Factors	Levels (Low Level / High Level)	Description
Objects	Continuous	**Velocity**	[1 , 3]	Nodes / time step
	Numerical	**Road Selection**	[1 , 2]	Objects choose road independent from each other (2) or have a single object per road (1)
	Continuous	**Time between Arrivals**	[1 , 40]	E[Time between Arrivals]
Agents (UAV)	Continuous	**Velocity**	[30 , 45 , 60]	Flight speed of the UAV (kts)
	Continuous	**Gamma**	[0 , 0.45 , 0.9]	Probabilities (identification)
	Continuous	**Rho**	[1-gamma , 0.45 , 1-gamma]	Probabilities (identification)
	Continuous	**Loiter Time**	[1 , 2]	Time steps for loitering
	Numerical	**Radius**	[250 , 1000]	Meters
Agents (QRF)	Continuous	**Deployment Threshold**	[0.7 , 1.0]	If threshold in any node is exceeded via Probability Map updating, then QRF will deploy to investigate that node
	Numerical	**Patrol**	[0 , 1]	Nodes away from FOB
	Continuous	**Clearing Time**	[1 , 2]	Time steps
	Numerical	**Prediction Model**	V1xP1 V1xP2 V1xP3 V2xP2 V2xP3 V3xP3	Cross matrix of object's velocity and prediction

Figure 8: Matrix depicting the factors and levels used for factor screening and Design of Experiments

Objects

Velocity – The object's velocity is modeled as a notional value and can take on one of three values and the bounds on these values are described in Figure 8. The object's velocity represents the time required to traverse from one node to the next adjacent node. Each value intends to simulate different types of objects whether they are foot traffic (3), vehicle on rough terrain (2), or vehicles on paved roads (1).

Road selection – The objects can be modeled in two different ways with respect to the roads selection process. This factor is categorical and can only take on one of two values, a single object per road or independent road selection. Modeling the objects as one object per road is the simpler technique due to the fact that only a single object travels down each road. Upon successful observation and identification of the threat, the threat can be interdicted rapidly; therefore minimizing any threat to the FOB. Modeling the objects road selection as independent from each other simulates reality since each object can travel down any road and is not dependent on the prior object's selection.

Time between arrivals – The arrival rates are modeled as a stochastic process where the inter-arrival times are exponentially distributed. With a time between arrivals of one time step, this represents all objects arriving in the AOI at nearly the same time. As the time is increased to five and eleven, the time separating the arrival of one object to the next is increased. As the time is increased, it is anticipated that the ease of interdicting the threat increases. Therefore with the maximum time used, an upper bound on how well the taskforce can perform can be studied

Agents (UAV)

Identification – These factors represent the sensor characteristics of the UAV. By varying the factors such that ρ (Rho) is the compliment of γ (Gamma) (identification) the lower diagonal of a detection or identification matrix may be evaluated. Modeling the imperfect sensor produces the same results from the upper versus the lower diagonal and therefore only one diagonal must be analyzed.

Loiter time – This factor represents the amount of time that the UAV remains at a single node for detection and identification operations. The levels that studied are a one and two time step loiter time. The one time step represents an observation that occurs in

one time step prior to moving to the next waypoint while the two time step represents a loitering to allow for a more time for an detection and identification operations.

Patrol radius – The UAV flies predetermined routes for each simulation run. This factor explores the variations in the response as the radius increases away from the FOB. The radii are measured as Euclidean distance from the FOB and provides insight into whether a farther detection range is better than performing more observations at a closer distance.

Agents (QRF)

Patrol – The QRF's patrol studied under a stationary context, as well as patrolling a single node away from the FOB. These distances provide quick response if a report is generated or if a threat is perceived to be close to the FOB. As the patrol distance is increased and the threat is traversing toward the FOB via a different road, then the QRF must traverse back to the FOB and then interdict the threat. The time that is required for the QRF to return to the FOB is additional time that the threat has to reach the FOB. Therefore, under these circumstances, there is an increased probability that the threat reaches the FOB if the patrol radius is increased dramatically.

Clearing time – This factor relates to the amount of time that is required to identify an object as a threat or not once the object is interdicted. Instantaneous clearing time takes a single time step to identify the object. The single-time step and a two-time step delay clearing time is evaluated. This time reflects the amount of time required to service the object once acquired. As the time is increased, the QRF remains with the object longer and therefore may have increased difficulty interdicting another object traversing down a different road may reach the FOB.

Prediction model – The prediction model is based on the perceived velocities of the objects through intelligence gathering. As information is gathered on the nominal traffic patterns and traffic flows of the objects, a prediction on where the objects are given their current location can be made. The prediction model is a Markov transition matrix that is studied against the object's true velocity based on the object motion model aforementioned within object velocity.

V1 represents an object's ability to transition from one node to the next adjacent node in one time step. V2 and V3 are synonymous with two and three time steps, respectively, to transition from one node to the next. The P represents the prediction model as described above where P1, P2 and P3 depict an object's motion based on of one, two or three time step transition from one node to the next adjacent node. The screening process explores all combinations of the velocities and the prediction models. These cross designs illustrate how well the intelligence gathered represents the true motion of the objects. The worst-case scenario is the V1xP3 or vise versa model since the objects true motion is a single time step to transition while the intelligence states that the objects tend to move every three-time steps. Therefore, utilizing the SASIO model, analysis on the importance of the intelligence gathered, as modeled by correctness of the motion model approximation, can be explored.

b. Response Variable and Justification

This thesis explores a number of factors and levels, which are illustrated in Figure 8. Through varying the objects and entities, the model can simulate the unpredictability of the objects and ultimately provide insight regarding employment tactics based on identifying the factors that have the most impact on the response.

Response variables

Percentage of threats interdicted **–** From the clearing list, the number of threats interdicted from each design point is obtained and the percentage of threats interdicted is calculated based on the number of replications used for each design point. Through analysis of this response, the factors based on enemy characteristics, as well as, Blue Force asset employment and characteristics can be obtained.

Time to interdict all threats **–** From the clearing list, the time that the objects were cleared is obtained. This response variable is explored to determine how many threats in the AOI are identified and cleared. Through measuring this response, the user can obtain better employment of the assets to maximize the number of threats

obtained. Along with the employment tactics, this response may provide insight into the

worst-case settings and necessity to request more assets in order to interdict all of the potential threats.

Distance the threats are interdicted with respect to the FOB **–** Since the purpose of this model is to provide insight into the tactics required to protect the FOB, an understanding of the distance that the threats are interdicted with respect to the FOB must be studied. Figure 9 illustrates these VBIED threats and their destruction radius varies based on the amount of explosives that the threat carries. Supposing that intelligence provides the type of vehicles utilized for VBIED based on recent attacks, the user can explore and/or predict the maximum the standoff distance obtainable with current assets using the SASIO simulation model. The analysis accounts for only the threats that are interdicted.

BATF Explosive Standards

ATF	Vehicle Description	Maximum Explosives Capacity	Lethal Air Blast Range	Minimum Evacuation Distance	Falling Glass Hazard
	Compact Sedan	500 pounds 227 Kilos (In Trunk)	100 Feet 30 Meters	1,500 Feet 457 Meters	1,250 Feet 381 Meters
	Full Size Sedan	1,000 Pounds 455 Kilos (In Trunk)	125 Feet 38 Meters	1,750 Feet 534 Meters	1,750 Feet 534 Meters
	Passenger Van or Cargo Van	4,000 Pounds 1,818 Kilos	200 Feet 61 Meters	2,750 Feet 838 Meters	2,750 Feet 838 Meters
	Small Box Van (14 Ft. box)	10,000 Pounds 4,545 Kilos	300 Feet 91 Meters	3,750 Feet 1,143 Meters	3,750 Feet 1,143 Meters
	Box Van or Water/Fuel Truck	30,000 Pounds 13,636 Kilos	450 Feet 137 Meters	6,500 Feet 1,982 Meters	6,500 Feet 1,982 Meters
	Semi-Trailer	60,000 Pounds 27,273 Kilos	600 Feet 183 Meters	7,000 Feet 2,134 Meters	7,000 Feet 2,134 Meters

Figure 9: Chart illustrating the Vehicle type with respect to the destructive capabilities based on the amount of explosives that can be carried, http://www.globalsecurity.org/military/intro/images/vbied-standards-chart.jpg

c. Design of Experiments

Experimental design is the purposeful control of the input factors to the experiment to obtain their relationship (if any) with the response variable (Montgomery,

2009). Through utilizing efficient techniques, information collection for analysis purposes can be obtained in the most cost-effective manner. Experimental design allows for the control of factors through simulation that would be difficult to control in reality. As an example, this simulation allows the programmer to control the rate at which threats arrive. In practice, this is an “uncontrollable” factor, but in the context of this simulation, it can be systematically changed and thus provide insights that would otherwise be unattainable.

Factor screening is the process of systematically varying the input factors in a way that allows the identification of the most influential with respect to the responses. The output from the screening provides the analyst with the main effect and interactions that are primarily driving the desired response variable. The design matrix contains 12 factors that are varied throughout the experiment

One method of exploring the factor space is through a full-factorial design, which is neither efficient nor desired due to the large number of experiments required. The number of experiments required to be performed utilizing 12 factors with 2 levels is 2^{12} or 4096 design points with zero replications. However, using the factor screening technique with fractional factorial design to examine main effects and 2^{nd}-order interactions, the number of runs can be reduced to 2^{k-p} where k is the number of factors and p is the number of generators. Therefore utilizing a fractional factorial design can reduce the number of design points to $2^{12-5} = 2^7 = 128$ design points.

Factorial designs are an effective and efficient method for designing experiments intended for factor screening. Fractional factorial designs provide a nice alternative to running full factorial designs because they provide information on main effects and low-order interactions in far fewer experimental tests. Note that linear regression is used to analyze the results from factorial designs. The classic factorial designs recommended for factor screening utilize only two levels of each input factor – a low level and a high level (Montgomery, 2009).

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III. FACTOR SCREENING: NUMERICAL ANALYSIS

Analysis was performed with respect to each response through a screening design and followed by cross-validation based on the influential factors obtained from factor screening. Often we are interested in determining what factors affect a particular response of interest. In order to accomplish this, we can design an experiment that allows us to estimate the magnitude and direction of the factor effects (such as main effects and two factor interactions). Factor effects describe numerically how much the response changes when each factor is changed. This type of experiment is called a screening experiment (and is sometimes referred to as a characterization experiment) (Montgomery, 2009). The process of screening the data for the three responses: (1) percentage of threats interdicted, (2) time to acquire threats and (3) distance with respect to the FOB that the threats were interdicted, is described within this chapter. This chapter discusses the results from the screening experiment for each of the three responses.

A. PERCENTAGE OF THREATS INTERDICTED

As discussed in Chapter II, counting the number of threats interdicted on a single design point and averaging that number based on 1000 replications of that design point, the percentage of threats interdicted can be obtained. The percentage of threats interdicted is a Bernoulli random variable, which takes the values, zero for not interdicted and 1 for interdicted by Blue Force. This response was transformed via a Log Odds, also known as the "logit" function, transformation to ensure the values remain between zero and one for the analysis is described below:

$$\text{Transformation} = \ln\left(\frac{\text{Percentage of threats interdicted}}{1-\ \text{Percentage of threats interdicted}}\right) = Y^{*} = x\beta + \varepsilon \qquad \text{(eqn. 3.1)}$$

Standard stepwise regression is performed in JMP (JMP, 2009). The linear regression model test the following hypothesis:

$$\begin{aligned} &\mathrm{H}_0 : \beta_0 = \beta_1 = \beta_{12} \ldots = \beta_n = 0, \quad \text{where } n \text{ is the number of coefficients} \\ &\mathrm{H}_A : \text{ at least one coefficient } \neq 0 \qquad \text{(eqn. 3.2)} \end{aligned}$$

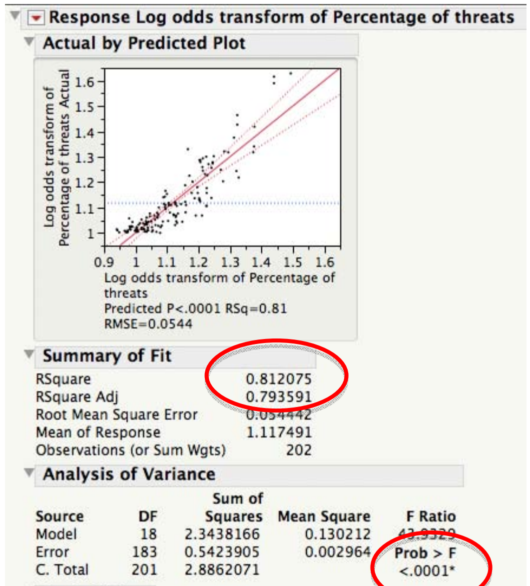
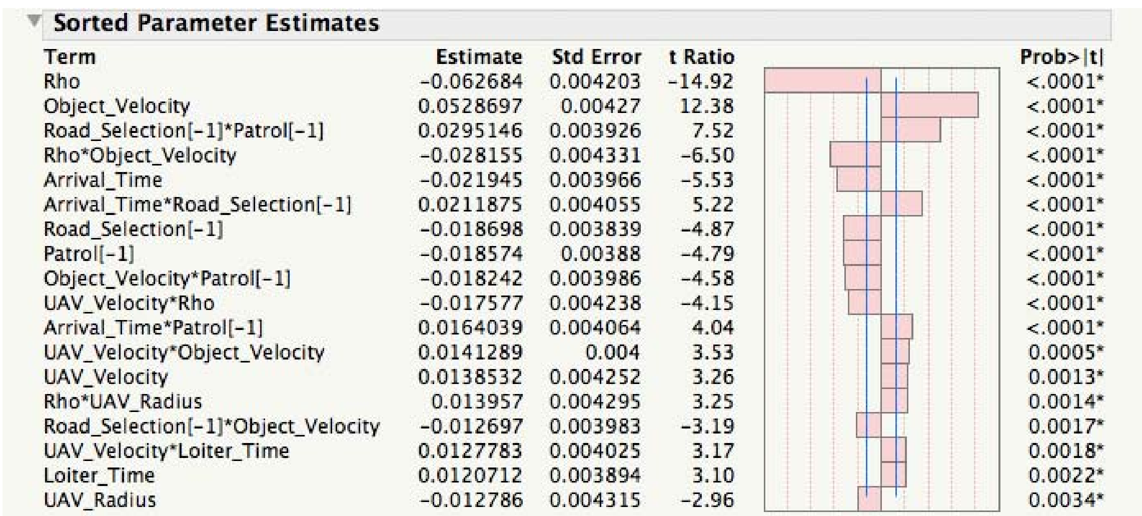


Figure 10: Linear regression model of Log Odds transformation of percentage of threats interdicted



Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Rho	-0.062684	0.004203	-14.92	<.0001*
Object_Velocity	0.0528697	0.00427	12.38	<.0001*
Road_Selection[-1]*Patrol[-1]	0.0295146	0.003926	7.52	<.0001*
Rho*Object_Velocity	-0.028155	0.004331	-6.50	<.0001*
Arrival_Time	-0.021945	0.003966	-5.53	<.0001*
Arrival_Time*Road_Selection[-1]	0.0211875	0.004055	5.22	<.0001*
Road_Selection[-1]	-0.018698	0.003839	-4.87	<.0001*
Patrol[-1]	-0.018574	0.00388	-4.79	<.0001*
Object_Velocity*Patrol[-1]	-0.018242	0.003986	-4.58	<.0001*
UAV_Velocity*Rho	-0.017577	0.004238	-4.15	<.0001*
Arrival_Time*Patrol[-1]	0.0164039	0.004064	4.04	<.0001*
UAV_Velocity*Object_Velocity	0.0141289	0.004	3.53	0.0005*
UAV_Velocity	0.0138532	0.004252	3.26	0.0013*
Rho*UAV_Radius	0.013957	0.004295	3.25	0.0014*
Road_Selection[-1]*Object_Velocity	-0.012697	0.003983	-3.19	0.0017*
UAV_Velocity*Loiter_Time	0.0127783	0.004025	3.17	0.0018*
Loiter_Time	0.0120712	0.003894	3.10	0.0022*
UAV_Radius	-0.012786	0.004315	-2.96	0.0034*

Figure 11: Relative significance of each factor based on a linear regression of the Log Odds transformation of percentage of threats interdicted.

Based on an F-statistic (p-value < .0001), shown in Figure 10, the null hypothesis is rejected using a .1 percent confidence level; therefore, at least one of the coefficients in the model is not equal to zero. Next, the R^2 value, denoted as Rsquared, has a value of 0.81 and Adjusted R^2, denoted as Rsquared Adj, has a value of 0.79 as shown in Figure 10. These values represent the amount of variability in the response that is explained by

this model and conclude that the model presented is a satisfactory linear model. Since this model is used to represent the data for the screening process, the factors that influence this response must be obtained. Figure 11 represents the relative weight of each factor that influences the response variable. For the purposes of this screening analysis, the top 20 percent of the total number of factors and interactions is chosen for the cross-validation analysis described in Chapter IV. Given the value of R^2 is high, the Pareto effect, which states that 80% of the results is due to 20% of the input, is the basis for choosing only 20% of the significant factors and allows for a minimum number of factors used in modeling to correctly and satisfactorily (neither over-fitting nor under-fitting the data) describe the data and are as follows:

- Rho
- Object velocity
- Road selection
- QRF patrol
- Inter-arrival time of the objects

Upon completion of analyzing the other responses, these factors, as well as the factors from the other responses is aggregated so that cross-validation and prediction analysis can be performed.

Figure 11 shows the relative weightings of each factor. The highest weighting factor is Rho, which directly relates to the classification of the threats by the UAV. This factor has a negative coefficient and therefore one can conclude that as one decreases this false negative identification error rate in the sensors, then the percentage of threats interdicted increases. That is, the better the sensor is at identification, then the better the chance of properly identifying the threat becomes (decreasing Rho by one unit increases the identification by 6%). The next factor is the object's velocity as the objects take longer to traverse from node to node then the probability of interdicting the threat also increases. Therefore, if the Blue Force can perturb the speed of the objects in the AOI, then there is a higher likelihood of interdicting the threat. The next factor is the interaction between road selection and patrol. If the Blue Force can utilize checkpoints to ensure that a single object traverses a road per a given timeframe along with performing patrols, then the threat is more likely to be obtained.

B. TIME TO ACQUIRE THREAT

The time to acquire the threat is defined as the time between a given threat's arrival into the AOI and its successful interdiction by the QRF. Using this calculated value as the response, a best-fit model is constructed based on 1000 replications to analyze the influential factors for this response.

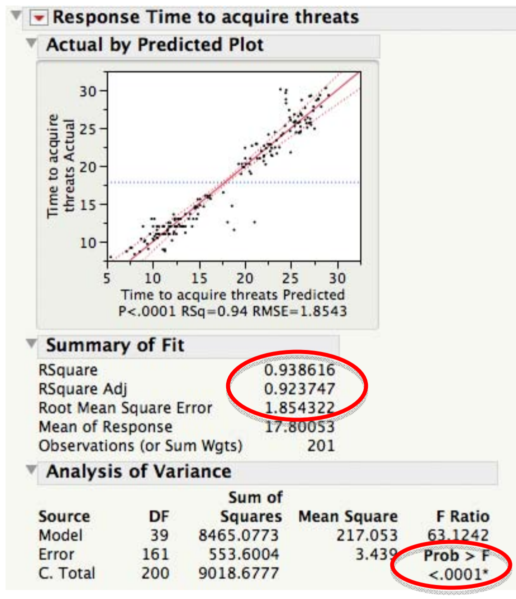
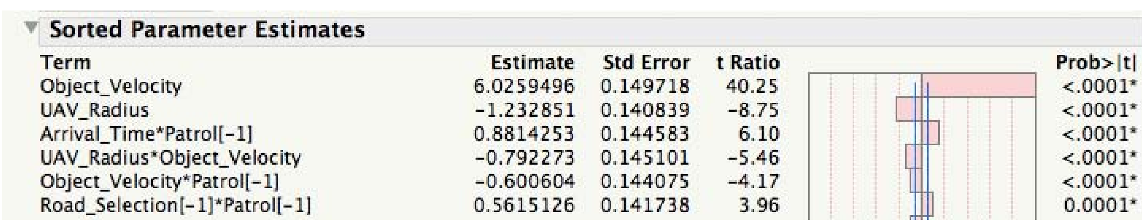


Figure 12: Linear regression model of the time to acquire threats



Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Object_Velocity	6.0259496	0.149718	40.25	<.0001*
UAV_Radius	-1.232851	0.140839	-8.75	<.0001*
Arrival_Time*Patrol[-1]	0.8814253	0.144583	6.10	<.0001*
UAV_Radius*Object_Velocity	-0.792273	0.145101	-5.46	<.0001*
Object_Velocity*Patrol[-1]	-0.600604	0.144075	-4.17	<.0001*
Road_Selection[-1]*Patrol[-1]	0.5615126	0.141738	3.96	0.0001*

Figure 13: The relative ordering of factors influencing the time to acquire threats

Based on an ANOVA hypothesis test, eqn. 3.3, the null hypothesis is rejected based on a F-statistic ($p < .0001$) and using a confidence level of .01%.

$$\mathrm{H}_0 : \beta_0 = \beta_1 = \beta_{12} \ldots = \beta_n = 0, \quad \text{where } n \text{ is the number of coefficients}$$
$$\mathrm{H}_A : \text{ at least one coefficient } \neq 0 \qquad \text{(eqn. 3.3)}$$

The R^2 =0.93 and Adjusted R^2 = 0.92 indicates that the model explains most of the variability of the response. The top 20% factors that influence the response are:

- Object Velocity
- UAV Radius
- QRF Patrol
- Inter-arrival Time of the Objects

Based on the factor weighting profile, Figure 13, the most significant factor is object velocity. As stated with percentage threats interdicted, if mechanisms such as speed bumps or checkpoints are used to perturb the object's speed, then the time to acquire the threat increases. Also, as the UAV radius is decreased, then the time to acquire the threat is decreased. This is potentially due to the UAV identifying more nearby threats while performing its operation and therefore issuing reports for the QRF to interdict.

C. MEAN DISTANCE AWAY FROM THE FOB

The mean distance away from the FOB that the threat was interdicted is calculated by observing the average distance that the threat was interdicted with respect to the FOB for each design point replicated 1000 times. A best-fit model was generated using this value as the response variable and the input factors as the regressors. The model for this analysis can be seen in Figure 14.

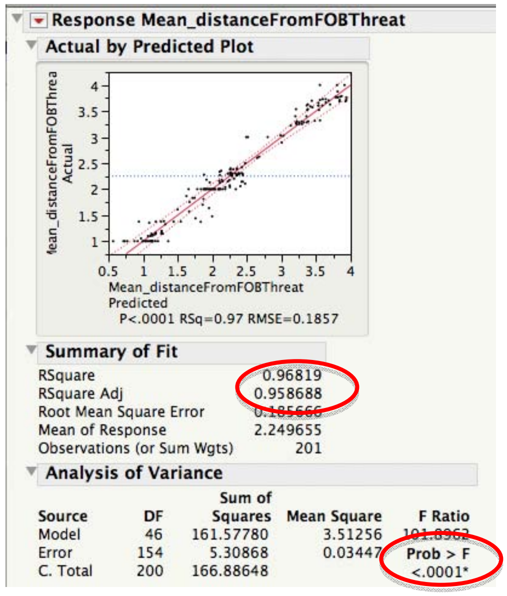


Figure 14: Linear regression model for mean distance from FOB

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Object_Velocity	0.6499086	0.01561	41.64	<.0001*
UAV_Radius	0.5071384	0.015844	32.01	<.0001*
Gamma*Rho	2.6714134	0.136129	19.62	<.0001*
Gamma	2.6558959	0.137283	19.35	<.0001*
Rho	2.6471123	0.137175	19.30	<.0001*
Object_Velocity*Patrol[-1]	0.1185227	0.014317	8.28	<.0001*
Patrol[-1]	0.1094159	0.014916	7.34	<.0001*
Arrival_Time*Patrol[-1]	-0.099192	0.014614	-6.79	<.0001*
Road_Selection[-1]*UAV_Radius	0.0945061	0.014652	6.45	<.0001*
UAV_Radius*Object_Velocity	0.0877332	0.014688	5.97	<.0001*
Road_Selection[-1]*Patrol[-1]	-0.082889	0.014048	-5.90	<.0001*
Arrival_Time*UAV_Radius	0.0817591	0.015208	5.38	<.0001*
Road_Selection[-1]*Object_Velocity	0.071135	0.01483	4.80	<.0001*
UAV_Radius*Patrol[-1]	0.0711642	0.014863	4.79	<.0001*
Road_Selection[-1]	0.0655551	0.01518	4.32	<.0001*

Figure 15: The relative ordering of the factors influencing the mean distance away from the FOB

The hypothesis testing for this model is as follows:

$$\mathrm{H}_0 : \beta_0 = \beta_1 = \beta_{12} \ldots = \beta_n = 0, \quad \text{where } n \text{ is the number of coefficients}$$

$$\mathrm{H}_A : \text{ at least one coefficient } \neq 0 \qquad \text{(eqn. 3.4)}$$

As before, the F-statistic (p-value < .0001) was calculated, which means that the alternative hypothesis is preferred over the null. By observing the R^2 =0.97 and the

Adjusted $R^2 = 0.96$, the conclusion that this model explains most of the variability in the response can be made. Therefore, using this model, the following factors are influential in the response variable:

- Object velocity
- UAV radius
- Gamma
- Rho
- QRF patrol

By looking at the weighting profile in Figure 15, Object velocity is the most dominate factor. Therefore, like the other response variables, if the object's speed was reduced, then the distance that the threat is interdicted is increased. Likewise, if the UAV's radius is increased, the chance to identify the threat at an increased distance means that the threat is interdicted by the QRF at an increased distance. Based on these findings, the employment of using the UAV at an increased radius is more beneficial to maximizing the distance to the FOB then one with a smaller radius.

D. CONCLUSION

Based on performing screening for each response, best-fit models were constructed. The models for each response had a high R^2 value, which suggests adequate fits from this analysis, each best-fit model was constructed and adequately modeled the response variables with respect to the factor inputs. The aggregated list of factors obtained from the above three models are utilized in further cross-validation and prediction analysis discussed in Chapter IV.

The list of factors (and associated responses) was aggregated together so that each response is using the same factor set. The reasoning for this is to create a prediction model based on all of the factors and to illustrate how each factor contributes to the response variables. As seen in Chapter IV, the SASIO model was run with intermediate design points related to these factors. Prediction models were then constructed to see how well these prediction models correctly represented the new data obtained from additional simulation runs.

	Responses		
Factors	% Threat interdicted	Time to acquire threats	Distance from FOB
Object velocity	X	X	X
UAV radius		X	X
Gamma			X
Rho	X		X
QRF patrol	X	X	X
Inter-arrival time of objects	X	X	
Road selection by the objects	X		

Table 1: List of influential factors based on the response variables

IV. DESIGN OF EXPERIMENTS: CROSS-VALIDATION

A. OVERVIEW

New design points were generated based on the findings of the screening exercise. The levels within this design include both the high and low levels of the factors, as well as intermediate values, which are then transformed into coded units as in the screening exercise for cross-validation. The design points (in engineering units) were then simulated in the SASIO model in order to explore each response variable in more depth. The prediction model formulated in the screening design is tested using cross-validation to see how well the prediction model performs.

B. CROSS-VALIDATION OF PREDICTION DATA

Based on a fractional factorial design of the input factors, 128 design points were created and half were used in cross-validation. Therefore, taking a subset of the prediction design points (random selection of 64) with the screening design points, a new prediction model was created. Through a visual representation of each response with their respective prediction models, analysis on the adequacy of the fit may be performed.

1. Percentage of Threats Interdicted

The significant factors for each of the response variables were used in creating the prediction models, Figure 16, for the percentage of threats introduced. The 202 (fractional-factorial design points created by JMP) design points from the screening exercise were joined with a random selection of 64 intermediate design points created for cross-validation. This set of 266 design points were then used to develop a prediction model based on the Log Odds transformation of the percentage of threats interdicted. The prediction equation, along with a 95% prediction interval, was then transformed back to percentage of threats so that an overlay graph could be created to analyze the percentage of threats interdicted. Figure 17 illustrates the prediction model with the remaining design

points. Each continuous factor has their associated coefficients, and for the numerical factors, the use of the Match statement is used depending on the level utilized.

$$
\begin{aligned}
&4.52 \\
&+ -0.22 * \mathit{Arrival\_Time} \\
&+ 7.48 * \mathit{Gamma} \\
&+ 6.44 * \mathit{Rho} \\
&+ \mathrm{Match}\left(\mathit{Road\_Selection}\right)\begin{cases} \text{"-1"} \Rightarrow -0.23 \\ \text{"1"} \Rightarrow 0.23 \\ \text{else} \Rightarrow . \end{cases} \\
&+ -0.16 * \mathit{UAV\_Radius} \\
&+ 0.57 * \mathit{Object\_Velocity} \\
&+ \mathrm{Match}\left(\mathit{Patrol}\right)\begin{cases} \text{"-1"} \Rightarrow 0.13 \\ \text{"1"} \Rightarrow -0.13 \\ \text{else} \Rightarrow . \end{cases} \\
&+ \mathit{Gamma} * \left(\mathit{Rho} * 7.56\right) \\
&+ \mathit{Rho} * \mathrm{Match}\left(\mathit{Road\_Selection}\right)\begin{cases} \text{"-1"} \Rightarrow -0.17 \\ \text{"1"} \Rightarrow 0.17 \\ \text{else} \Rightarrow . \end{cases} \\
&+ \mathit{Rho} * \mathrm{Match}\left(\mathit{Patrol}\right)\begin{cases} \text{"-1"} \Rightarrow -0.12 \\ \text{"1"} \Rightarrow 0.12 \\ \text{else} \Rightarrow . \end{cases} \\
&+ \mathrm{Match}\left(\mathit{Road\_Selection}\right)\begin{cases} \text{"-1"} \Rightarrow \mathrm{Match}\left(\mathit{Patrol}\right)\begin{cases} \text{"-1"} \Rightarrow 0.14 \\ \text{"1"} \Rightarrow -0.14 \\ \text{else} \Rightarrow . \end{cases} \\ \text{"1"} \Rightarrow \mathrm{Match}\left(\mathit{Patrol}\right)\begin{cases} \text{"-1"} \Rightarrow -0.14 \\ \text{"1"} \Rightarrow 0.14 \\ \text{else} \Rightarrow . \end{cases} \\ \text{else} \Rightarrow . \end{cases} \\
&+ \mathit{Object\_Velocity} * \mathrm{Match}\left(\mathit{Patrol}\right)\begin{cases} \text{"-1"} \Rightarrow -0.21 \\ \text{"1"} \Rightarrow 0.21 \\ \text{else} \Rightarrow . \end{cases}
\end{aligned}
$$

Figure 16: Prediction model equation for Log Odds transformation for percentage of threats interdicted

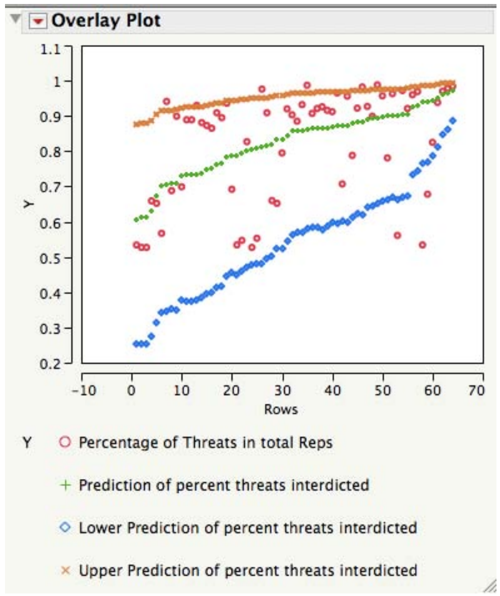


Figure 17: 95% prediction model fit for the percentage of threats interdicted with an overlay plot of the data obtained from a subset of the sensitivity design points

Figure 17 illustrates that there are nine data points that fall outside the 95% prediction interval, which equate to 14% of the cross-validation data points. Analysis of the dominant factor, object velocity, indicates that the data points, which fall above the upper prediction interval primarily had the fastest speed, while those that fell below the lower limit had the slower speed. From this insight, sub-analysis is performed to create a prediction model based on the individual speeds (1, 2 or 3), thereby providing recommendation on employment strategies based on the terrain profiles that constrain the object's velocity.

2. Time to Acquire Threats

The set of 266 design points, 202 from the screening exercise and 64 from the sensitivity design points were used to create a prediction model for the response variable, i.e., time to acquire threats. This process of cross-validation was utilized to achieve a more accurate prediction model, Figure 18, by incorporating intermediate factor levels that were concluded to be significant from the screening design. Based on this linear

regression model, the prediction model with a 95% prediction interval was constructed. The remaining 64 sensitivity design points were then overlaid on this prediction plot as shown in Figure 19.

$$
\begin{aligned}
&16.08\\
&+ -0.41 * \mathit{Arrival\_Time}\\
&+ -1.58 * \mathit{Gamma}\\
&+ -1.72 * \mathit{Rho}\\
&+ \text{Match}\left(\mathit{Road\_Selection}\right)\begin{cases} \text{"-1"} \Rightarrow -0.08 \\ \text{"1"} \Rightarrow 0.08 \\ \text{else} \Rightarrow . \end{cases}\\
&+ -0.98 * \mathit{UAV\_Radius}\\
&+ 6.28 * \mathit{Object\_Velocity}\\
&+ \text{Match}\left(\mathit{Patrol}\right)\begin{cases} \text{"-1"} \Rightarrow -0.22 \\ \text{"1"} \Rightarrow 0.22 \\ \text{else} \Rightarrow . \end{cases}\\
&+ \mathit{Arrival\_Time} * \left(\mathit{Rho} * 0.19\right)\\
&+ \mathit{Arrival\_Time} * \left(\mathit{UAV\_Radius} * -0.28\right)\\
&+ \mathit{Arrival\_Time} * \text{Match}\left(\mathit{Patrol}\right)\begin{cases} \text{"-1"} \Rightarrow 0.76 \\ \text{"1"} \Rightarrow -0.76 \\ \text{else} \Rightarrow . \end{cases}\\
&+ \mathit{Gamma} * \left(\mathit{Rho} * -1.64\right)\\
&+ \mathit{Rho} * \left(\mathit{Object\_Velocity} * -0.21\right)\\
&+ \mathit{Rho} * \text{Match}\left(\mathit{Patrol}\right)\begin{cases} \text{"-1"} \Rightarrow -0.62 \\ \text{"1"} \Rightarrow 0.62 \\ \text{else} \Rightarrow . \end{cases}\\
&+ \text{Match}\left(\mathit{Road\_Selection}\right)\begin{cases} \text{"-1"} \Rightarrow \mathit{UAV\_Radius} * -0.29 \\ \text{"1"} \Rightarrow \mathit{UAV\_Radius} * 0.29 \\ \text{else} \Rightarrow . \end{cases}\\
&+ \text{Match}\left(\mathit{Road\_Selection}\right)\begin{cases} \text{"-1"} \Rightarrow \text{Match}\left(\mathit{Patrol}\right)\begin{cases} \text{"-1"} \Rightarrow 0.52 \\ \text{"1"} \Rightarrow -0.52 \\ \text{else} \Rightarrow . \end{cases} \\ \text{"1"} \Rightarrow \text{Match}\left(\mathit{Patrol}\right)\begin{cases} \text{"-1"} \Rightarrow -0.52 \\ \text{"1"} \Rightarrow 0.52 \\ \text{else} \Rightarrow . \end{cases} \\ \text{else} \Rightarrow . \end{cases}\\
&+ \mathit{UAV\_Radius} * \left(\mathit{Object\_Velocity} * -0.68\right)\\
&+ \mathit{Object\_Velocity} * \text{Match}\left(\mathit{Patrol}\right)\begin{cases} \text{"-1"} \Rightarrow -0.44 \\ \text{"1"} \Rightarrow 0.44 \\ \text{else} \Rightarrow . \end{cases}
\end{aligned}
$$

Figure 18: Prediction model equation for time to acquire threats

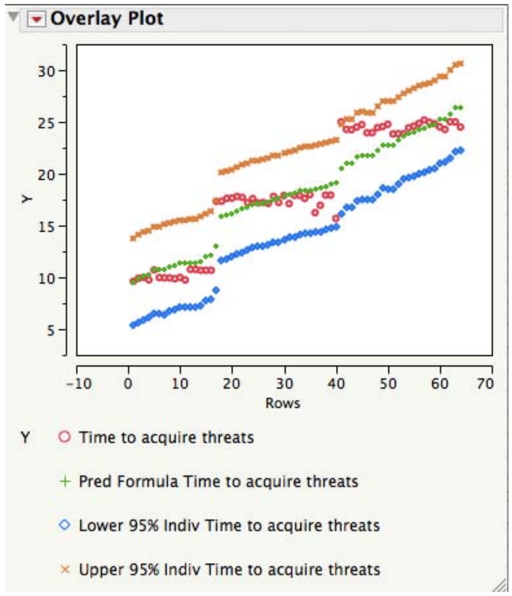


Figure 19: 95% prediction model fit for the time to acquire threats with an overlay plot of the data obtained from a subset of the sensitivity design points

Figure 19 shows all of the design points fall within the prediction interval bounds. Based on this graph, the prediction model constructed using the described technique is an adequate prediction model. As seen in the graph, there are three distinct levels of the data points, a lower, intermediate and an upper level. Each of these levels is due to the influence of the object's velocity. The lower segment correlates to the objects having a faster speed while the upper segment is the objects with the slower speed. The reasoning is that the objects travel toward the FOB at a faster rate and therefore take a shorter amount of time before being interdicted. Likewise, the objects that travel toward the FOB at a slower rate are acquired in a longer period of time.

3. Mean Distance to FOB

The same techniques used for creating the prediction model for the time to acquire the threat response was used for mean distance to FOB. Figure 20 represents the prediction model based on the best-fit linear regression model and the subset of cross-validation points were overlaid on this prediction model for further analysis illustrated in Figure 21.

$$
\begin{aligned}
& 2.14 \\
& + 0.075 * \mathit{Arrival\_Time} \\
& + -0.02 * \mathit{Rho} \\
& + \mathrm{Match}\left(\mathit{Road\_Selection}\right)\begin{pmatrix} \text{"-1"} \Rightarrow 0.08 \\ \text{"1"} \Rightarrow -0.08 \\ \text{else} \Rightarrow . \end{pmatrix} \\
& + 0.39 * \mathit{UAV\_Radius} \\
& + 0.6 * \mathit{Object\_Velocity} \\
& + \mathrm{Match}\left(\mathit{Patrol}\right)\begin{pmatrix} \text{"-1"} \Rightarrow 0.08 \\ \text{"1"} \Rightarrow -0.08 \\ \text{else} \Rightarrow . \end{pmatrix} \\
& + \mathit{Arrival\_Time} * \mathrm{Match}\left(\mathit{Road\_Selection}\right)\begin{pmatrix} \text{"-1"} \Rightarrow -0.05 \\ \text{"1"} \Rightarrow 0.05 \\ \text{else} \Rightarrow . \end{pmatrix} \\
& + \mathit{Arrival\_Time} * \left(\mathit{UAV\_Radius} * 0.08\right) \\
& + \mathit{Arrival\_Time} * \left(\mathit{Object\_Velocity} * 0.07\right) \\
& + \mathit{Arrival\_Time} * \mathrm{Match}\left(\mathit{Patrol}\right)\begin{pmatrix} \text{"-1"} \Rightarrow -0.09 \\ \text{"1"} \Rightarrow 0.9 \\ \text{else} \Rightarrow . \end{pmatrix} \\
& + \mathit{Rho} * \left(\mathit{UAV\_Radius} * -0.06\right) \\
& + \mathit{Rho} * \left(\mathit{Object\_Velocity} * -0.06\right) \\
& + \mathit{Rho} * \mathrm{Match}\left(\mathit{Patrol}\right)\begin{pmatrix} \text{"-1"} \Rightarrow 0.08 \\ \text{"1"} \Rightarrow -0.8 \\ \text{else} \Rightarrow . \end{pmatrix} \\
& + \mathrm{Match}\left(\mathit{Road\_Selection}\right)\begin{pmatrix} \text{"-1"} \Rightarrow \mathit{UAV\_Radius} * 0.06 \\ \text{"1"} \Rightarrow \mathit{UAV\_Radius} * -0.06 \\ \text{else} \Rightarrow . \end{pmatrix} \\
& + \mathrm{Match}\left(\mathit{Road\_Selection}\right)\begin{pmatrix} \text{"-1"} \Rightarrow \mathit{Object\_Velocity} * 0.05 \\ \text{"1"} \Rightarrow \mathit{Object\_Velocity} * -0.05 \\ \text{else} \Rightarrow . \end{pmatrix} \\
& + \mathrm{Match}\left(\mathit{Road\_Selection}\right)\begin{pmatrix} \text{"-1"} \Rightarrow \mathrm{Match}\left(\mathit{Patrol}\right)\begin{pmatrix} \text{"-1"} \Rightarrow -0.08 \\ \text{"1"} \Rightarrow 0.08 \\ \text{else} \Rightarrow . \end{pmatrix} \\ \text{"1"} \Rightarrow \mathrm{Match}\left(\mathit{Patrol}\right)\begin{pmatrix} \text{"-1"} \Rightarrow 0.08 \\ \text{"1"} \Rightarrow -0.08 \\ \text{else} \Rightarrow . \end{pmatrix} \\ \text{else} \Rightarrow . \end{pmatrix} \\
& + \mathit{UAV\_Radius} * \left(\mathit{Object\_Velocity} * 0.07\right) \\
& + \mathit{UAV\_Radius} * \mathrm{Match}\left(\mathit{Patrol}\right)\begin{pmatrix} \text{"-1"} \Rightarrow 0.07 \\ \text{"1"} \Rightarrow -0.07 \\ \text{else} \Rightarrow . \end{pmatrix} \\
& + \mathit{Object\_Velocity} * \mathrm{Match}\left(\mathit{Patrol}\right)\begin{pmatrix} \text{"-1"} \Rightarrow 0.08 \\ \text{"1"} \Rightarrow -0.08 \\ \text{else} \Rightarrow . \end{pmatrix}
\end{aligned}
$$

Figure 20: Prediction model equation for mean distance to FOB

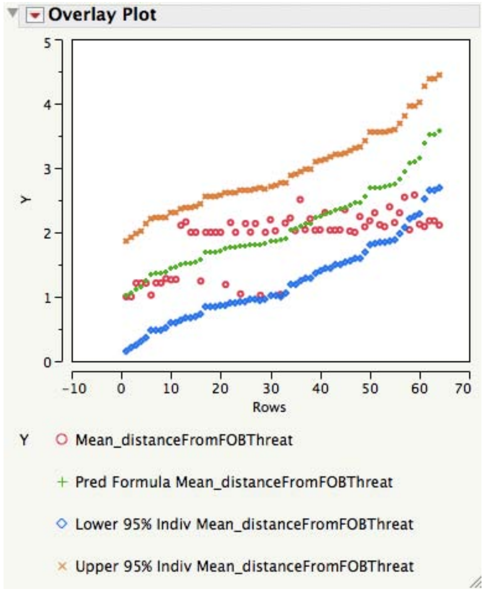


Figure 21: 95% prediction model fit for the mean distance to FOB with an overlay plot of the data obtained from a subset of the sensitivity design points

Figure 21 illustrates that there are six data points that fall outside the lower prediction interval, which equate to 9% of the 64 sensitivity design points. Further investigation of the characteristics of these design points represents the influence of the interaction between patrol and object velocity. If the QRF does not patrol, i.e., remains stationary at the FOB, and the object's speed is the slowest, then the resulting data fell outside the lower confidence bound. Since the QRF does not perform an interdiction unless either a report is issued by the UAV or the threat is within the surveillance region of the QRF, then for the six design points, further analysis must be performed to see if the results presented in Figure 19 are due to variability in the model.

4. Conclusion

The prediction models presented based on a cross-validation technique provided adequate models for each of the response variables. Further analysis must be performed for percentage of threats (Figure 17) interdicted based on the object's velocity. Through follow-on analysis, an employment strategy that incorporates perturbing the object's velocity may provide an increased efficiency in predicting the interdiction of threats.

The model that was developed for the time to acquire threats (Figure 19) adequately fit the subset of additional simulation experiments. Through the analysis that explores the impact of object velocity, better prediction models may be developed. Through this analysis, insights regarding each significant factor and relative influence may be explored.

The prediction model (Figure 20) provides insights with respect to the interaction between object velocity and the QRF's patrol employment strategy. The prediction interval used an alpha level of 0.05, which means that there is a 5% chance of committing a Type I error. Since a 95% prediction interval is created, then the prediction interval should encapsulate 95% of the data. Further analysis should either conclude that the 9% of the design points that were outside of the lower prediction band for mean distance to FOB was either due to noise, or that this influence is significant enough to impact the simulation. Based on current analysis, this differentiation cannot be concluded and is resolved with additional analysis.

C. EXPLORATION OF OBJECT'S VELOCITY WITH RESPECT TO EACH RESPONSE

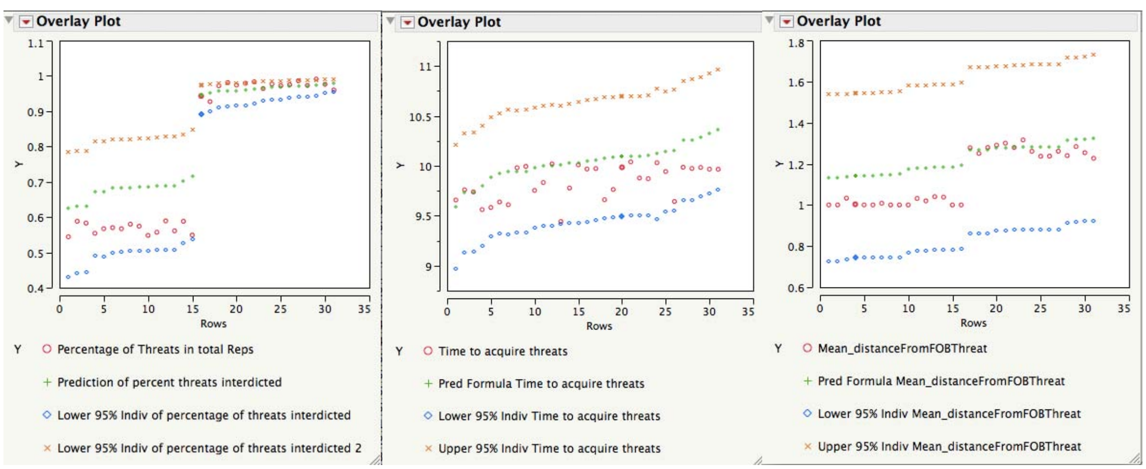
Due to a small percentage of data points falling outside of the prediction intervals, further analysis was performed to glean insight into the behavior of the simulation. The prediction models were created based on fixing the object's velocity at one, two and three and performing analysis on each of these data sets. A linear regression model was created and a prediction model was obtained. A subset of each of the object's velocity design points was reserved to fit with the prediction models. The analysis and insights obtained from utilizing this technique follow.

1. Object Velocity Fixed at the Maximum Speed

The figures below represent each of the prediction models with their respective responses overlaid. Figure 22 shows that all of the data points for the object's velocity fixed at the maximum velocity fall within the 95% prediction interval derived. Some useful insights can be obtained from these pictures by observing that there appears to be

two distinct data intervals in Figure 22A. This is due to the patrolling characteristics of the QRF, the lower data set being the QRF is patrolling and the upper set of data is the QRF; remaining at the FOB. Therefore, from this insight, if the AOI cannot be altered to reduce the speed of the object, then the QRF should remain at the FOB. Another factor that influences the results is the inter-arrival time of the objects. By choosing an AOI that minimizes the traffic flow or by establishing checkpoints to minimize the incoming objects, then the Blue Force can acquire more threats.

Figure 22C also shows two distinct data intervals, which is due to whether the QRF patrols or not. If the QRF's employment technique is to patrol, then the standoff distance from the FOB is increased; conversely, if the QRF remains at the FOB, then the standoff distance is decreased. Therefore, the QRF patrolling affects both the percentage of threats interdicted, as well as the mean distance to FOB; however, the benefits of one is detrimental to the other.



(A) (B) (C)

Figure 22: 95% prediction model fit for the (**A**) percentage of threats interdicted, **(B)** time to acquire threats, (**C)** mean distance from FOB with an overlay plot of the data obtained from a subset of the fixed maximum speed design points

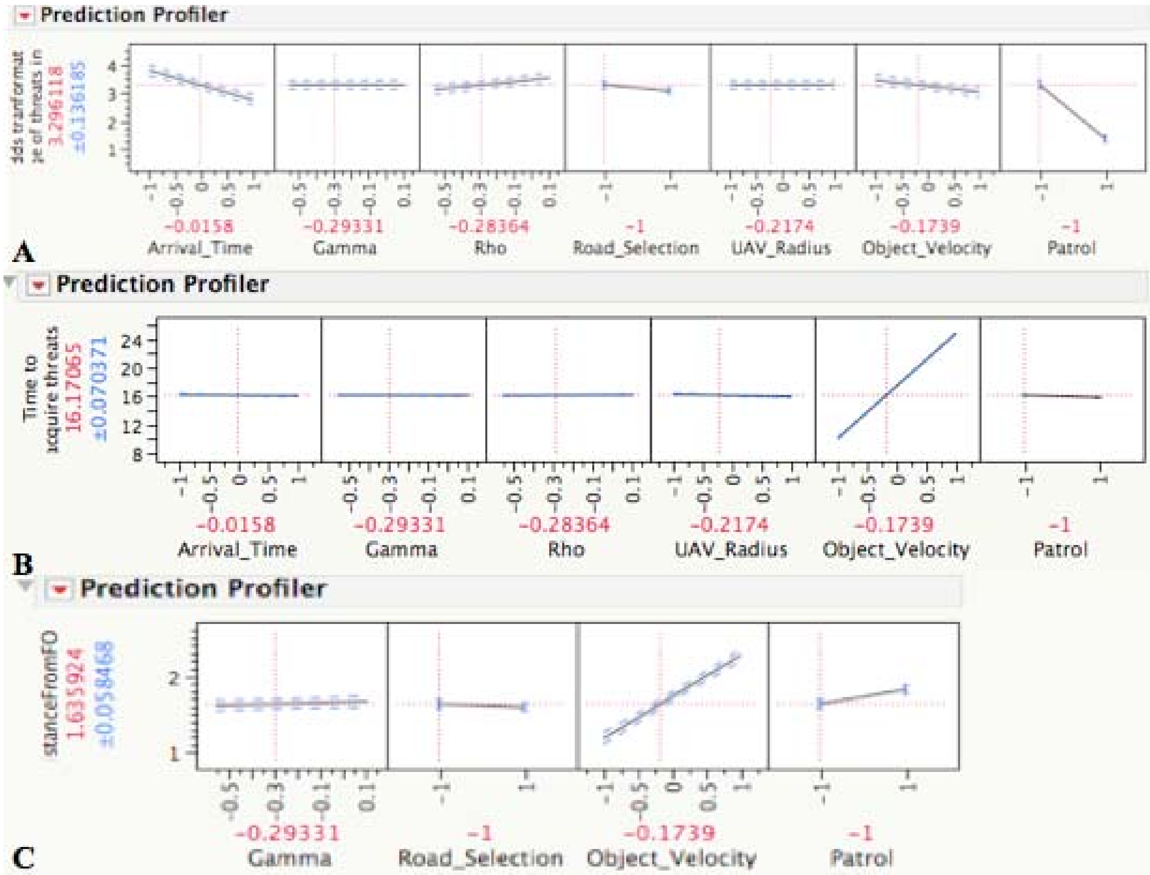


Figure 23: Prediction profiler for (**A**) Log Odds transformation for percentage of threats interdicted, (**B**) time to acquire threats, (**C**) mean distance from FOB

Figure 23 illustrates the prediction profiler for each response variable. Figure 23A shows that the dominant factor for the percentage of threats interdicted is whether the QRF patrols (1) or not (-1). For both the time to acquire (Figure 23B) threats and mean distance from FOB (Figure 23C), the dominant factors are object velocity and QRF patrol. Based on this analysis, techniques to reduce the object's velocity increases the time to acquire the threats as well as increase the standoff distance from the FOB. Also, Figure 23C illustrates that if the QRF patrols, then the standoff distance is maximized.

Analysis of the model with the objects at their maximum speed, the dominating factor is the object's velocity. To ensure that a large number of threats are interdicted, the QRF should remain stationary at the FOB. However, if the commander wants to maximize the standoff distance to the FOB, then a patrolling QRF should be employed.

Through this analysis, a trade-off exists between interdicting threats or maximizing the standoff distance and an understanding of the impact of choosing one over the other must be made clear.

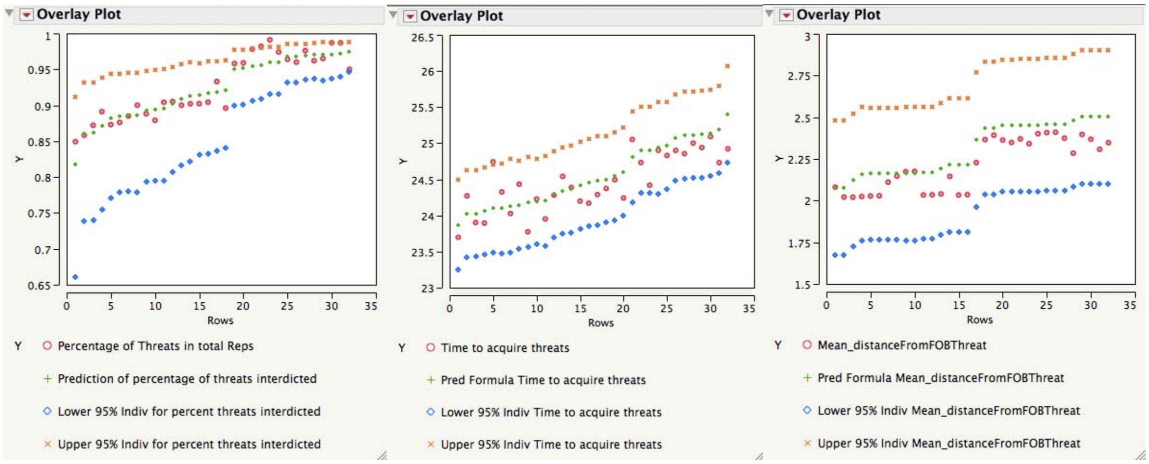
2. Object Velocity Fixed at the Slowest Speed

In this study, the SASIO model simulated the design matrix fixing the object’s velocity to the minimum value. Taking a subset of this output with the cross-validation design matrix, techniques were used to create a linear-regression model. Figure 24, shows that all but one data point fall within the prediction model and one can conclude that the prediction models are adequate.

One notes that there are two distinct cases represented in Figure 24A, as with the object’s velocity set to the maximum speed. By using the prediction profiler (Figure 25A) in conjunction with the prediction plot, the most significant factor is whether the QRF patrols or not. The insights obtained from this analysis are that the QRF should remain stationary at the FOB to interdict most of the threats. Like the analysis performed for the maximum object speed, the AOI should be chosen or checkpoints should be established to minimize the traffic flow to the FOB.

The 95% prediction model (Figure 24B) adequately predicts the data created by minimizing the object velocity. The prediction profiler (Figure 25B) demonstrates that the most significant factor remains object velocity. This follows that if an object is slow, then the time to acquire this threat increases. This is due to the increased time between the object entering into the AOI and an interdiction report being made.

From the analysis performed with respect to the mean distance from FOB, the prediction model adequately predicts the data. Two distinct cases arise in this graph and they are due to whether the QRF patrols or not. If the QRF remains stationary at the FOB, then the mean distance from the FOB is decreased as shown in Figure 25C. However, if the QRF patrols, then the standoff distance is maximized.



(A) (B) (C)

Figure 24: 95% prediction model fit for the (**A**) percentage of threats interdicted, **(B)** time to acquire threats, (**C**) mean distance from FOB with an overlay plot of the data obtained from a subset of the fixed maximum speed design points

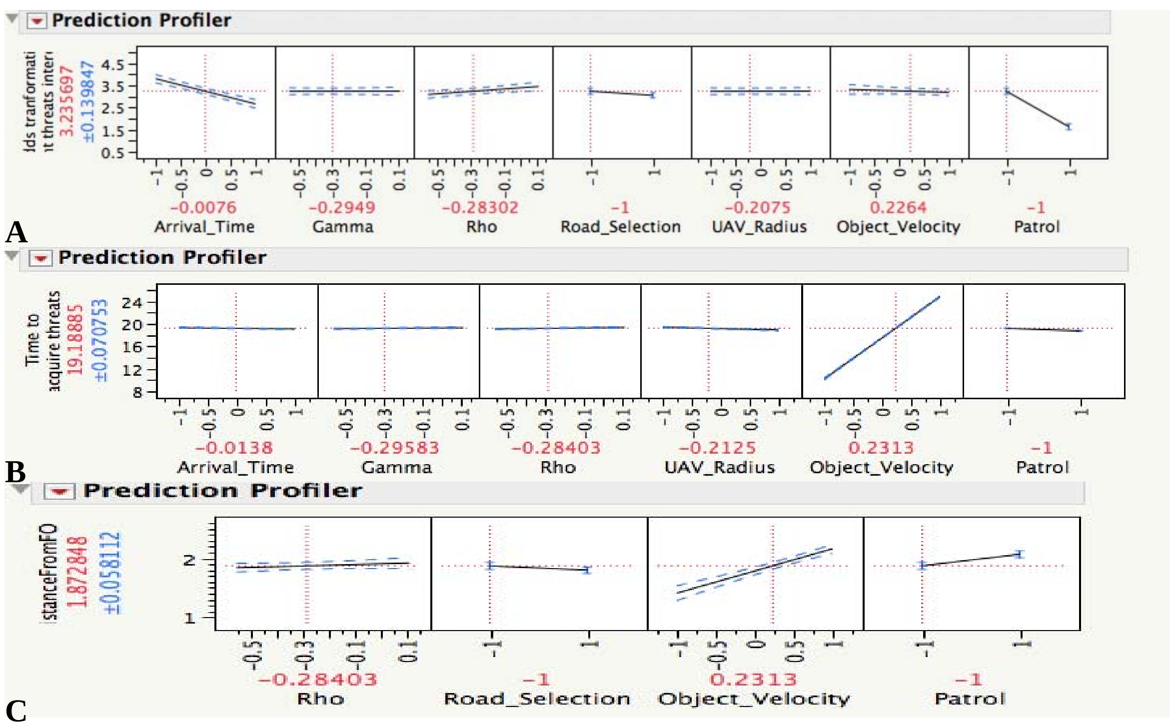


Figure 25: Prediction profiler for (**A**) Log Odds transformation for percentage of threats interdicted, (**B**) time to acquire threats, (**C**) mean distance from FOB

V. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSIONS

The factors being used for this analysis should be categorized in two groups: factors that are controllable (Blue Force employment techniques) and those that are uncontrollable (enemy tactics). Once the factors are broken down into these groups, the Blue Force employment techniques can be better explored to maximize the percentage of threats interdicted, minimize time to interdict these threats, and maximize the distance from the FOB the threats are interdicted, as well as seek methods to best disrupt the enemy's tactics.

1. Blue Force Employment

When using the UAV, having sensors with minimal errors results in an increased identification rate. This factor has a minor effect on influencing the percentage of threats interdicted. This is due to the ability of the UAV to provide an increased identification range (i.e., increased standoff identification) and can aid the commander in properly responding to a threat prior to its arrival at the FOB.

The next employment technique is to decide whether the QRF should patrol or not. Based on the analysis, the percentage of threats interdicted decreases if the QRF patrols; however, the time till interdiction decreases with patrols and the mean distance to FOB is maximized as the QRF patrols. The former effect is potentially due to the QRF searching a different road while performing its patrol and not being able to perform surveillance on the other road. There is a larger decrease in the percentage of threats interdicted over the benefits gained in time to interdict or mean distance to FOB. Based on having only a single QRF to patrol, one would recommend maintaining the QRF stationary until either a report is issued by the UAV or observed by the QRF while in close proximity to the FOB.

Based on the insights provide by the model, the Blue Force can successfully perform its operation utilizing a single QRF and UAV. More analysis must be performed on the effect of an increase in number of UAVs and QRF units employed. However, preliminary consideration of utilizing multiple UAVs lead to recommendations such as to employ the UAVs at maximal distance to ensure rapid identification. If there are two QRFs, then based on the analysis, the commander should allow one QRF to patrol the area, while maintaining one QRF at the FOB. This allows for FOB protection with the stationary QRF while an increased interdiction range with the patrolling QRF.

2. Blue Force Actions External to Current Assets

The predominate threat factor is the speed at which the object travels down a road. As the speed is increased, then all three responses are degraded. Therefore, based on this analysis, the Blue Force can set up blockades or other obstacles in order to reduce the speed at which all objects traverse down the road.

The other factor that the Blue Force can influence is the road selection of the objects. If each road is limited to travelling down a single road, then each response increases in the Blue favor. Setting up checkpoints prior to the entrance into the AOI can counteract this problem. These checkpoints can be provided by the indigenous population that can provide intelligence to the Blue Force, but whose primary goal is to perturb the flow of traffic down each road.

B. ONGOING RESEARCH

Ongoing research, which utilize SASIO model framework, studies the potential improvement in effectiveness by increasing the available surveillance and interdiction assets. Another study utilizing the SASIO model framework is a game-theoretic approach that encompasses an adversarial threat and potential strategies to combat these threats. The study explores current Blue Force strategies and compares those strategies with possible improvements based on an effective use of surveillance and interdiction assets.

The current SASIO model implementation requires either utilizing command-line arguments or a graphical user interface (GUI) to run the program. Current work is to

continue to evolve the GUI interface as new concept and/or ideas arise such as: switching from a screening design to sensitivity analysis, implementing the desired number of replications, and choosing the scenario based on user inputs. As seen in Figure 26, the GUI is currently used for the SASIO scenario posed in this thesis; however, the evolution of this program allows an easy to command shell to execute tactical scenarios.

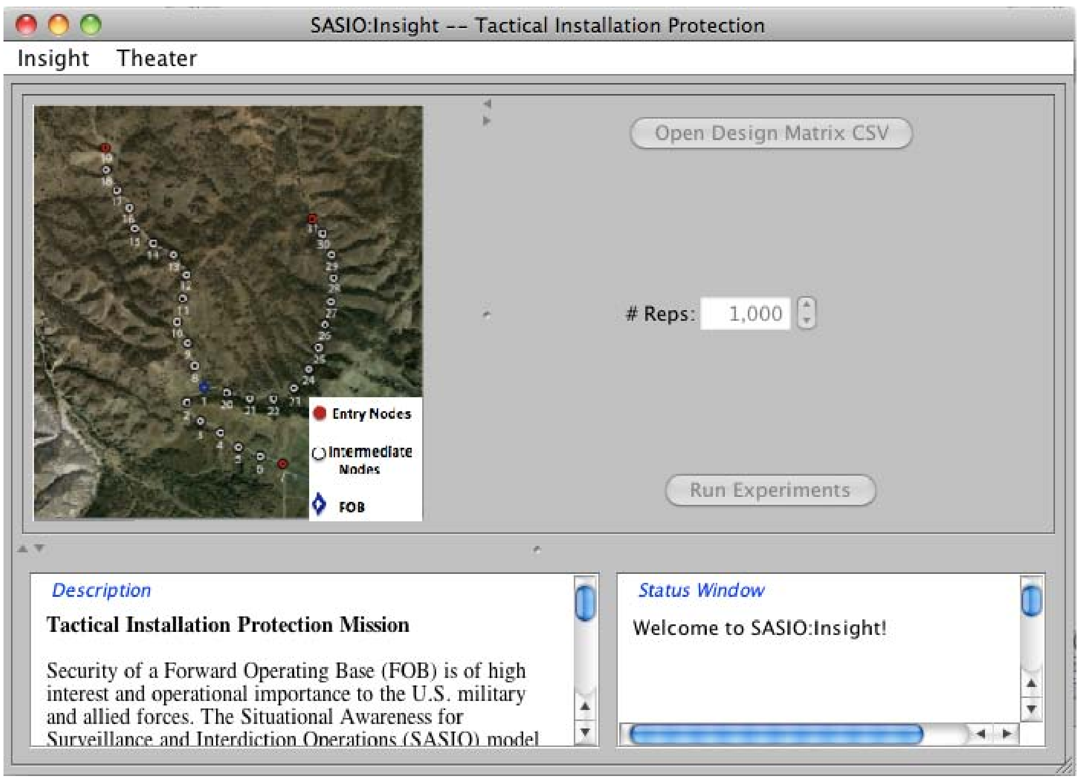


Figure 26: SASIO tactical installation protection graphical user interface

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